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Poet-Composer Collaborations in Modern Egyptian Song: A Social Network Analysis Approach to Music History

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In this paper I formulate and apply a social network analysis methodology for understanding the history of song on Egyptian radio. Music is a massively relational cultural form, involving interactions among composers, poets, arrangers, conductors, and performers, among others. The reality of music history thus emerges as a complex network of relationships, unfolding and changing over time. Song production, in particular, centers on poet-composer-singer collaborations. Many Arab music histories highlight narratives of the stars, presented in historical and cultural context, but neglect the broader network of productive relationships. However many important musical figures are not celebrities, and the full complexity of the non-linear network can only be grasped holistically, including big data empirical analysis, not pointillistically through case studies of celebrities. Such holistic analysis can reveal surprising emergent, structural patterns that are not apparent in any single narrative. Social network analysis (SNA) offers a powerful suite of tools enabling such an approach, including metrics for centrality and the detection of cohesive subgroups. Starting with a large dataset of songs broadcast on Egyptian radio, I extract a network of poet-composer collaborations, and apply SNA algorithms to reveal its social structure. I then interpret that structure in light of wider socio-cultural and historical factors. In this way, my paper both sheds light on Egypt's musical history, and supplies a model and method that may be applied, mutatis mutandis, to other musical domains.

I. Introduction

A. The history of music, music history, big data, and social network analysis

How do we transform the history of music into music history? How well do prevailing modes of historiography reflect musical reality? Music emerges from social interactions interconnecting myriad agents, for music is a collaborative art, arising from, as well as forging, relationships. Occasional appearances to the contrary, individuals never make music alone. But celebrities loom large in music culture, especially since the emergence of media technologies and the music industry. Music histories are thus prone to telling linear stories of star composers or performers. Such histories lie far from music's expansive, tangled reality, because they are both reductive and

atomizing. To understand the full social complexity of musical life requires both big data, and relational data, combining to form large social networks representing musical interactions.

Taking a broad view of music to include all "musicking" (Small), this network should include myriad roles: composers, poets, performers, arrangers, conductors, and producers, as well as dancers, impresarios, venue managers, distributors, broadcasters, critics, audiences, consumers, and listeners generally. Ideally, musical historiography would include the representation of countless collaborations among all these musical participants, unfolding over time. Such a task would be impossible, even for relatively well-documented music.

But in every place and time certain roles are more important to musical production than others. Modern Arab music centers on precomposed song, produced primarily by relationships connecting poets, composers, and singers. How can we understand Arab music history by applying social network analysis (SNA) to composer-poet collaborations? My paper aims to answer this methodological question.[1]

Most music histories do not adopt a big data approach, in the past perhaps because such data was not readily available. But the advent of the modern music industry both radically altered musical reality, and generated the big data to describe it. Here, I define musical modernity in technological terms. Recording and broadcasting drew a bright historical line, utterly transforming the musical landscape, from the introduction of the phonograph in the late 19th century, to radio and musical films, TV, LPs, cassettes, and CDs, down to contemporary music streaming services. Alongside these technological transformations came seismic shifts in the modes and relations of music production, from a small-scale live performance art, to a complex music industry founded on technologies of recording and dissemination. The Arab world was no exception (Malm; Frishkopf, *Music and Media*).

The same factors producing musical modernity, technology and industrial complexity, both enabled and required the construction of large music databases, yielding big data. Technologies for media recording, transmission, dissemination, and archiving offered the *possibility* for cataloging such data, while music's embedding in an industrial system *necessitated* it, for the sake of tracking production, distribution, and sales; intellectual property management; accounting of royalties and taxes; and sometimes government censorship. Thus, big data emerged out of both technological possibilities and administrative need.

For example, Egyptian radio has broadcast music, of different styles and eras, ever since its founding in 1934 (El-Shawan, "The Socio-Political Context of al-Musika al-ʿarabiyyah in Cairo, Egypt: Policies, Patronage, Institutions, and Musical Change (1927-77)"). In order to locate recordings of suitable length, genre, and personnel, to properly announce them, and to transfer use statistics to performing rights organizations, it was essential to catalog them. Once computer technology provided the means, large song databases were developed containing metadata, including song title, and the names of collaborating singer, composer, and poet, as well as the date and duration of the recording. Such song lists provide an excellent starting point for social network analysis of musical relationships, as I will demonstrate in this paper, and they are crucial for understanding modern Egyptian musical history, due to the centrality of state radio throughout the middle third of the 20th century, at least until the cassette era of the late 1970s, and even thereafter (Castelo-Branco; Boyd; Fahmy).

However, resistance to big data representations of music history stems also from a particular methodological disposition. The prevailing music historical norm among academic musicologists has been to critically interpret "small data", a relatively limited number of salient cases, even if conceptually embedded within a wider cultural landscape. In an earlier era music historians centered their studies almost entirely upon biographies of a relatively small, select group of music's "great men" and their works, typically excluding women, but also deemphasizing the social connections that actually constitute music culture. While a narrative appreciation of key figures and works may be necessary to attain a humanistic understanding of music history, such an approach is insufficient for a sociological one.

Since the 1990s, following the rise of Postmodern, New, or Cultural Musicology (Kramer), musicologists have broadened their scope to cultural studies, considering music practices more critically within a wider socio-musical space beyond "great" individuals and works, supported by diverse disciplinary perspectives—gender studies, political economy, post-colonial studies, or ecology (Rehding; Solie; Qureshi; Locke)—broadening the canon, but without entirely relinquishing attachment to the concept of musical luminaries. Small data non-relational qualitative study has remained central to musicology, albeit now embedded in a wider context.

More recently, there have been counter-trends. Particularly since the late 1990s' advent of social media, many music scholars began to deploy the "social network" concept as a potent metaphor, though mostly without its development as an empirical object of investigation (Ozment). In ethnomusicology, always more attuned to the social, scholars have applied social network concepts qualitatively to diagram small groups (Brinner; Frishkopf, "Music for Global Human Development: Participatory Action Research for Health and Wellbeing"). With the increasing prominence of

digital humanities in the late 2000s, quantitative big data computational empirical musicology and ethnomusicology has made a confident appearance as well (Gómez et al.; Weyde et al.; Kent-Muller; Urberg; Abdallah et al.; Cottrell; Clercq). But most of this research centers on datasets populated with bibliographic, catalogue, score, transcription, or audio data, and associated metadata, rather than on the social networks underlying music production, though some bibliographic studies have included techniques of network analysis (Rose et al.).

Social network analysis requires big social data – and near-complete data. Such data is not always easily obtained. Missing data and consequent issues of imputation are thorny compared to those of conventional non-relational statistics, and constitute an enormous problem for social network analysis (Krause et al.; Kossinets). Perhaps in part for this reason SNA musicological studies are scarcer, though the literature is growing (see Giannetti). Nick Crossley and his colleagues have made numerous contributions (McAndrew and Everett; Crossley, *Networks of Sound, Style and Subversion*; Crossley, "Music Worlds and Event Networks"; Crossley and Ozturk; Crossley and Ozturk; O'Shea). Scholars from math, physics, and engineering, working in the new sciences of network and complexity studies, and bringing stronger technical skills for data collection and analysis, have delved deepest into musical SNA, studying large networks of musical influence, similarity, and collaboration, though mainly in Western music, where data is more readily available (Gienapp et al.; Zhang et al.; Park et al.; Ortega; Bryan and Wang).

Arab music has not lagged much, if at all, in absorbing new technologies and modes of music production. The earliest Egyptian recordings date to around 1904 (Racy, "Record Industry and Egyptian Traditional Music" 25), numerous radio stations were active in Cairo from the 1920s, musical film emerged in 1932, and national radio in 1934 (El-Shawan, "The Socio-Political Context of al-Musika al-'arabiyyah in Cairo, Egypt: Policies, Patronage, Institutions, and Musical Change (1927-77)" 94, 97; Fahmy). Consequently, music changed rapidly as well, in both its sonic and social aspects. Traditional Egyptian music of the 19th and early 20th centuries—later known as the *turath* (heritage)—centered on poetry set to melodies based on a system of modes (the *maqamat*) and meters (the *iqa'at*), accompanied by a small heterophonic chamber ensemble. Within this repertoire, the precomposed metric song, featuring classical or colloquial Arabic poetry, was central. Instrumental pieces and improvisations served primarily as preludes or transitions. But vocal improvisation – particularly the *mawwal* and *qasida* – was also important, and in any case the singer was typically the composer as well – often accompanying him or herself on the oud (a type of fretless lute). A series of pieces in a common mode constituted a longer suite, the *wasla*, whose performance might require an hour or more (Lagrange; Racy, "Music in Nineteenth-Century Egypt: An Historical Sketch"; Racy, "Waslah").

Starting from the early 20th century, new media technologies dramatically altered this musical scene, though certain elements were retained. Within the Arab world, Egyptian music remained in the vanguard, due to the country's large population, central location, proximity and openness to Europe, and status as a cultural hub. Transformations wrought by technological innovations along with corresponding changes in modes of production hit Egypt first, and most forcefully (Racy, *Musical Change and Commercial Recording in Egypt, 1904-1932*).

Retentions from the older *turath* included a continued focus on song, with lyrics and hence singer central, in contradistinction to the greater prominence of instrumental genres in other Middle Eastern musics, particularly Turkey and Iran. But with the advent of a capitalist media economy requiring a consistently polished product, and due to length restrictions (the phonograph cylinder could only hold around two minutes of music; 78s only slightly longer), precomposed songs soon became the norm. Improvisation declined, and ensembles expanded, necessitating carefully prepared arrangements. All of these factors led to greater specialization. The centrality of precomposed song meant that distinct figures of composer and poet were now central as well, and increasingly separated from roles of singer, instrumentalist or (later) arranger or producer (Frishkopf, *Music and Media*).

Arab music histories remain primarily rooted in the older school of small data critical interpretation, often centered on lives of the "great" singers and composers. Those written in Arabic are particularly prone to such tendencies, perhaps because the limited market for such works is primarily a popular one, fascinated by celebrity. Books surveying a wider swath of musical history typically present a series of capsule biographies, whether covering the modern period, or stretching back over a thousand years to the legendary, swashbuckling figure of Ziryab (Zaki, *A'lam al-Musiqa al-Misriyya 'abr 150 sana*; Zaki, *al-Mu'asirun min Rawwad al-Musiqa al-'Arabiyya*; Mursī; Najmi; Darwish; Sahab).

Several recent scholarly studies in English likewise focus upon a single celebrated performer or composer (Danielson; Zuhur; Frishkopf, "Nationalism, Nationalization, and the Egyptian Music Industry"), though contextualized within cultural history. Other English-language studies present broader social histories of music, transcending a focus on the individual, yet remaining largely in the camp of small data, qualitative interpretation, centered upon prominent individuals, though Salwa El-Shawan's scholarly oeuvre presents some quantitative analyses as well (Racy, "Sound and Society: The Takht Music of Early-Twentieth Century Cairo"; Racy, "Music in Nineteenth-Century Egypt: An Historical Sketch"; El-Shawan, "Western Music and Its Practitioners in Egypt (ca. 1825-1985): The Integration of a New Musical Tradition in a Changing Environment"; El-Shawan, "The Socio-Political Context of al-Musika al-'arabiyyah in Cairo, Egypt: Policies,

Patronage, Institutions, and Musical Change (1927-77)"). Again, Brinner's exemplary study of Israeli and Arab musicians applies social network theory, but in a qualitative, small data manner. Without a doubt, all these works contribute importantly to Arab music history, and yet small data limitations mean that they also miss emergent patterns that can only be discerned through a big data social network analysis approach.

Indeed, the lack of a big data, inclusive, and relational approach to music history means that salient features of the music network may be overlooked entirely. For instance, to foreshadow my own conclusions: never in all my readings on Arabic music did I encounter mention of the most productive collaboration in mid-20th century Egyptian song: that of lyricist Hussein al-Sayed (1916 - 1983) and composer Mohamed Abdel Wahab (1901 – 1991). Individually these figures are well known (though only Abdel Wahab shines in music history). But the fact that theirs was the most productive partnership in modern Egyptian song is not, because this fact is not traversed in any individual narrative. Yet it is an important fact of Egyptian music history, due to the centrality of relationship in the production of the musical art. Using a big data SNA approach, facts such as this one immediately pop out, ripe for interpretation.

To summarize: two primary problems afflict music historiography, masking salient features of music history, and particularly in the Arab world: a tendency to interpret a small number of cases, i.e. a *lack of big data*, and a tendency to atomize: a *lack of relational data*. These problems can be ameliorated simultaneously by collecting and analyzing large quantities of relational data: big social networks.

In this paper I outline an SNA approach to Arab music historiography, predicated on the mid-20th century social and musical centrality of Egyptian state radio and the modern concept of the fully precomposed Arabic song. This approach comprises two phases: (1) assembly and analysis of a social network representing musical collaborations between poets and composers, thereby highlighting salient facts and suggesting key questions, and (2) interpretation of these facts and pursuit of these questions, by situating the network within a wider social, cultural, and historical context. I apply (1) to highlight key agents and structures of Egypt's modern musical history, based on big relational data, while leaving (2) to the future. In the process, beyond any specific conclusions that may be drawn, I aim to illustrate a transposable method that might be applied, *mutatis mutandis*, elsewhere.

B. Social Network Analysis[2]

Social network analysis (SNA) begins with an abstraction: the concept of network, of broad applicability to many real-world problems. Formally, a network is a set of nodes, together with a set of links. Each link (or tie) can be defined as a pair of nodes, whether ordered or unordered. The pair is thus connected, and each node is said to be a neighbor to the other. The ordered pair (a,b) represents an asymmetric directed link *pointing* from node a to node b, while the unordered set {a,b} represents a symmetric undirected link *joining* a and b. A network containing directed links is called a directed network. While every link connects exactly two nodes, one at either end, a node can be connected by any number of links. In principle two nodes might be connected by many links, but in a so-called "simple" network at most one link connects each node pair. A node's *degree* is the number of links by which it is connected, which—in a simple network—is the same as the number of its neighbors.[3]

A network is highly abstract, but it admits of many useful real-world interpretations. Social network analysis centers on networks for which nodes and links are given social interpretations. Nodes typically represent social agents (people or organizations), while links represent relations between those agents – undirected for reciprocal relations (such as "consanguinity", "collaborating with") and directed for non-reciprocal relations (such as "admires", "teacher of").

Nodes and links have properties, represented by numbers. Some of these properties are derived from network structure (e.g. a node's degree); others, sometimes called "attributes", are derived from the network's real-world interpretation (e.g. a node's gender) rather than structure. Links are often associated with a property called "weight", typically indicating its strength. An unweighted network is formally equivalent to a weighted network in which all weights are equal to 1; these are used interchangeably. A node's weighted degree is the sum of the weights of the links to which it is connected. In general degree and weighted degree are different. But if an

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2 The roots of social network analysis lie in the sociometry of Jacob Moreno and others, dating to the 1930s. The field blossomed in the 1970s; Freeman provides an excellent history (Moreno; Freeman, *The Development of Social Network Analysis: A Study in the Sociology of Science*). Over the past 20 years a broader and increasingly popular field, network science, has emerged as a productive theoretical and methodological approach to formulating and solving problems across a wide range of disciplines, from physical and biological sciences to ecology, medicine, psychology, sociology, linguistics, business, and technology, especially as the online world, both hardware and software, is explicitly formulated in these terms (e.g. computer networks, social media networks). Correspondingly, a wide range of books on the topic have appeared in recent decades, some devoted to to network science in general (Newman; Barabasi, *Network Science*), and others to social network analysis in particular (Wasserman and Faust; Scott; Nooy et al.), as well as numerous popular science treatments (Barabasi, *Linked*; Watts; Christakis and Fowler). At the root of it all lies the mathematical theory of graphs (Biggs et al.; Wilson). Rather than trace this history, my presentation in this introductory section draws on these sources to succinctly sketch SNA's principal ideas, in a manner simple enough to be understood by any reader, yet sufficient to enable comprehension of the analysis that follows.

3 To avert possible confusion it is useful to note, at the outset, that mathematicians employ a different terminology: for them, networks are *graphs*, nodes are *vertices*, directed links are *arcs*, and undirected links are *edges*. Some social network researchers define a network as a graph representing real-world phenomona, and hence augmented with a social context, and metadata: numerical attributes associated with vertices, edges, and arcs, but not derivable from the mathematical structure itself. (Nooy and et al. 8)

unweighted network is exchanged for its weighted equivalent, degrees in the former will match weighted degrees in the latter. When n multiple, unweighted links connect two nodes they can be replaced by a single link of weight n without loss of information. Replacing all such multiple links across an unweighted non-simple network results in an equivalent weighted, simple network.

A network in which any two nodes can be connected is called "one-mode": its nodes are homogeneous with respect to connection. Such a network can be represented by a square table, or matrix, with an equal number of rows and columns. The nodes are numbered and listed to the left of the first column, and above the first row. Then the presence of a directed link from node m to node n is indicated by writing the link's weight (or "1" for an unweighted network) into the cell located in row m and column n. If the network is undirected, we use the lower left triangle only, since cells in the upper right triangle represent the same node pairs.

While a network can be represented geometrically – in two, three, or higher dimensions – in theory, spatial layout is immaterial for representing its structural properties. But visualization is exceedingly valuable for understanding and interpretation, due to the acuity of our visual sense, and our ability to recognize visual patterns. The abstract network structure can be physically instantiated and visualized as a set of balls (representing nodes) connected by strings (links), such that each string connects exactly two balls. For directed links the string is assigned a beginning and end.

More practically, we may also draw the network on a flat piece of paper, using circles (or any closed shape) for nodes and lines for links. For directed links, direction can be indicated by an arrowhead. Node and link properties may also be visualized as, for instance, node area or line thickness (for quantitative properties), or color (for qualitative ones).

But because only connections matter, all visual representations are accurate so long as connections are drawn correctly. Three nodes connected in triangular formation with three links can be represented as an equilateral triangle of any size, or a scalene triangle with three lengths at different orders of magnitude entirely: a millimeter, a meter, and a kilometer. (Of course it is important for the drawing to fit on a page!)

However, among all drawings that fit, some are far more useful as visualizations than others. For the sake of visualizing network structure it is helpful to draw a network so as to represent the relative importance of each node and link. Since link crossings are meaningless (only link-node connections are significant), visualizations strive to minimize them (crossings mistakenly imply that the point of intersection is important), as well as to ensure that structurally central nodes are visually central too (rigorous definitions of node centrality will follow). In an unweighted network, all

links should be of roughly equal length (if higher weight indicates a stronger connection, e.g. more frequent collaboration, then weightier links should be shorter).

One way to optimize a network drawing is to apply a force-directed layout algorithm. Such algorithms, of which several are well-known, take each link to be a spring with fixed natural length. When compressed to become shorter, or stretched to become longer, the spring exerts a contrary force, roughly proportional to the change in length, thus requiring that energy be expended, stored as potential energy in each compressed or stretched spring.[4] Nodes can be also be modeled as positively charged particles that repel each other when not connected, tending to reduce inadvertent line crossings. Using an iterative physical simulation, the layout algorithm determines node positions so as to minimize total potential energy, i.e. maintaining link lengths as close as possible to their neutral (unstretched) state and increasing distance between nodes not connected by a link. The simulation halts when adjustments are no longer reducing energy, or after a maximum run time.

Since rotations and translations do not affect total energy, the resulting positioning will not be absolute but only relative. Furthermore simulation of this physical process must begin with random positioning. Another factor determining the final positioning of nodes is simulation length. For all these reasons, different runs may produce different results. Two commonly used force-directed layout algorithms are Kamada-Kawai, and Fruchterman-Reingold. Either may be set to account for link weights, such that shorter strings model stronger links. (Kobourov; Kamada and Kawai; Fruchterman and Reingold)

A undirected network may be connected or disconnected; a connected piece is called a component. Representing the network using balls and fixed-length strings, lifting a single ball raises the entire component to which it belongs.[5] Note that a component could be as small as a single disconnected node; conversely, the entire network may comprise a single component.

In this study, I represent song production data as a network by assigning each artist (poet or composer) a distinct network node, and each unique song an undirected link connecting its poet and its composer, representing a single collaboration. For the preliminary analysis described in this paper I do not include any other artists (singers or instrumentalists) in the network. Every node has a binary attribute, indicating its role: poet or composer. Artists who fulfill both roles (i.e. serving as both poet and composer) are represented by two different nodes. Clearly this network is not simple, since a collaborating pair (poet and composer) frequently produce several songs together, leading

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4 The approximation that a spring's force is proportional to its stretching or compression is known as "Hooke's Law" (Feynman, vol 2, 38-1).

5 The definition is slightly more complex for directed networks.

to multiple links between the two. But we can replace such multiple links with a single weighted link, thereby arriving at an equivalent simple weighted network, as explained earlier.

The resulting network is also bipartite, or "two-mode", because the set of nodes can be divided into two types or "modes" (here, poet nodes, and composer nodes), such that every link connects an element of one set to an element of the other. This result follows from the definitions, since every collaboration connects a composer and poet (and since an individual functioning as both poet and composer is assigned two different nodes corresponding to the two roles). Whereas a one-mode network can be represented by a square matrix, a two-mode or bipartite network is better represented as a rectangular matrix with m rows and n columns, where m is the number of nodes in the first mode (e.g. poets) and n is the number of nodes in the second mode (e.g. composers). Every cell in such a network represents a possible collaboration. (See Borgatti and Everett)

Earlier I mentioned that there are several ways of evaluating node centrality. In this paper, I deploy five centrality metrics: (1) Degree centrality, (2) Weighted degree centrality, (3) Closeness centrality, (4) Betweenness centrality, and (5) Eigenvector centrality. (See Nooy and et al. ch. 6; Freeman, "Centrality in Social Networks Conceptual Clarification"; Wasserman and Faust, ch. 5)

Degree and weighted degree centrality have already been introduced. Recall that link weight represents the number of collaborations between a composer and a poet. Then degree centrality measures an artist's total number of collaborators, while weighted degree centrality measures the artist's total number of collaborations (songs).

For two other kinds of centrality—closeness and betweenness—we require additional network concepts of geodesic, and geodesic distance. An (undirected) walk between two network nodes N_1 and N_n is a sequence N_1, L_1, N_2, L_2, N_3, L_3.... N_{n-1}, L_{n-1}, N_n such that the N's are nodes, the L's are links (for this definition, we'll ignore link direction, if any), and the sequence is connected: L_1 links N_1 and N_2; L_2 links N_2 and N_3, and so on, down to L_{n-1} which links N_{n-1} and N_n. The length of such a walk is the number of links it contains (here, n-1). Since this number is an integer, there must be a shortest length walk between N_1 and N_n (though there may be more than one walk of this length). Each such shortest length walk is called a geodesic, and its length is the geodesic distance between N_1 and N_n. The geodesic distance is well-defined for two nodes in the same component; for two nodes in different components there is no walk connecting them. Then we can either say that the geodesic distance is undefined, or that it is infinite.

The closeness centrality of node N is the reciprocal of the average distance from N to all other nodes, equivalent to the number of other nodes divided by the sum of its geodesic distance to each of them. Those that are closer, on average, to all other nodes, rendering the denominator smaller, will display a higher closeness centrality value. To compute node N's betweenness centrality, consider all *pairs* of other nodes. Each such pair may be connected by one or more geodesic. For each such geodesic we may ask: does it pass through N? N's betweenness centrality is the fraction that do. Note that to compute closeness centrality a network must be connected, comprising a single component. Betweenness centrality, however, can be computed for any network, connected or not.

Finally, eigenvector centrality is a recursive metric: the centrality of a node N depends on the centrality of its neighbors. Link weight can also be taken into account, such that high link weights imply greater centrality. I will not present the mathematical details, but they are available online for those who are interested.[6]

II. SNA for Egyptian music history

A. Egyptian song data as a social network

Like other media institutions, Egypt's public broadcaster, the Egyptian Radio and Television Union (*Ittiḥād al-Idhāʿa wa al-Tilifīzyūn al-Miṣrī*) maintains a database of their their musical recordings, for programming and intellectual property rights (IPR) management, since song creators must receive royalties. Each database record contains a song title, as well as the names of composer, poet, and singer, along with other relevant information. A song may appear in the database more than once, due to multiple recordings by the same singer, or by different singers.

We can easily convert such a database into a weighted network. First we clean the tabular data, standardizing spellings and names, and correcting any typographical errors. A single artist or song must have a single name, and if two artists or songs have the same name they must be differentiated, so that there is a one-to-one mapping between artists and songs, and the names used to identify them in the database. Next we enhance the data, detecting and correcting factual errors as much as possible, and adding missing data wherever possible.

After removing incomplete records, there remain 14,020 completely documented recordings. However, multiple rows – with identical composer, poet, and title – may correspond to the same song. These may be covers

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6 All network operations and visualizations were executed using the free Pajek software package; see http://mrvar.fdv.uni-lj.si/pajek/ (Nooy and et al.). On the advice of one of Pajek's co-authors, Andrej Mrvar, I am using Pajek's "hubs and authorities" 2-mode algorithm for computing eigenvector centrality in the two-mode poet-composer network. (Batagelj and Mrvar)

Table 1. The first 10 of 12,523 complete records, each representing a unique song recording held by Egyptian Radio.

Record	Song	Singer	Poet	Composer
1	حفتكرلك ايه	محمد فوزي	مصطفى عبد الرحمن	محمد فوزي
2	ادي الحياة	فايزة احمد	عمر بطيشة	محمد سلطان
3	بنت الحب	ميادة الحناوي	عمر بطيشة	خليل مصطفى
4	آخر زمن	ميادة الحناوي	سمير الطائر	محمد سلطان
5	حكاية حب	ميادة الحناوي	عصمت الحبروك	سيد مكاوي
6	ست الكل	فايدة كامل	حسين السيد	محمد الموجي
7	عيني	ميادة الحناوي	عمر بطيشة	محمد سلطان
8	فاتت سنة	ميادة الحناوي	سيد مرسي	بليغ حمدي
9	قد ايه واحشني	عادل مأمون	عبد العزيز سلام	عادل مأمون
10	يا مصر ياجنة	فاطمة علي	حيدر إمام	كامل احمد علي

by different singers, or different recordings by one singer, or even erroneous multiple entries for exactly the same recording. We only want to count each song once, regardless of how many recordings exist, whether by the same or different singers.

We therefore run a duplicate detection algorithm, identifying groups of rows for which song title, composer, and poet are identical, and replacing them with a single row. After removing the duplicate rows, each of the remaining rows in the database represents a distinct song, the output of a collaboration between a poet and a composer (who are nearly always different people, and contemporaries). Thus reduced, the database contains 12,523 unique songs, the first ten of which are presented in Table 1.

Finally we can construct a preliminary bipartite "two-mode" network, interpreting every song as a link connecting its poet and composer (singers are not included in the analysis). Multiple links between a given poet and composer are then replaced by a single link whose weight is equal to the number of song collaborations connecting them. Each node's *degree* then represents the number of its *collaborators* (composers for poets; poets for composers), while its *weighted degree* represents the number of its *collaborations* (songs).

B. The full network

VISUALIZING AND COUNTING

To visualize this network, I apply a force-directed algorithms, Fruchterman-Reingold, to generate a representation in three dimensions, presented in two-dimensional projection in Figure 1. (The layout can also be viewed in 3D using the video link provided in the caption.) Poet nodes are yellow; composer nodes are green; collaboration links are blue.)
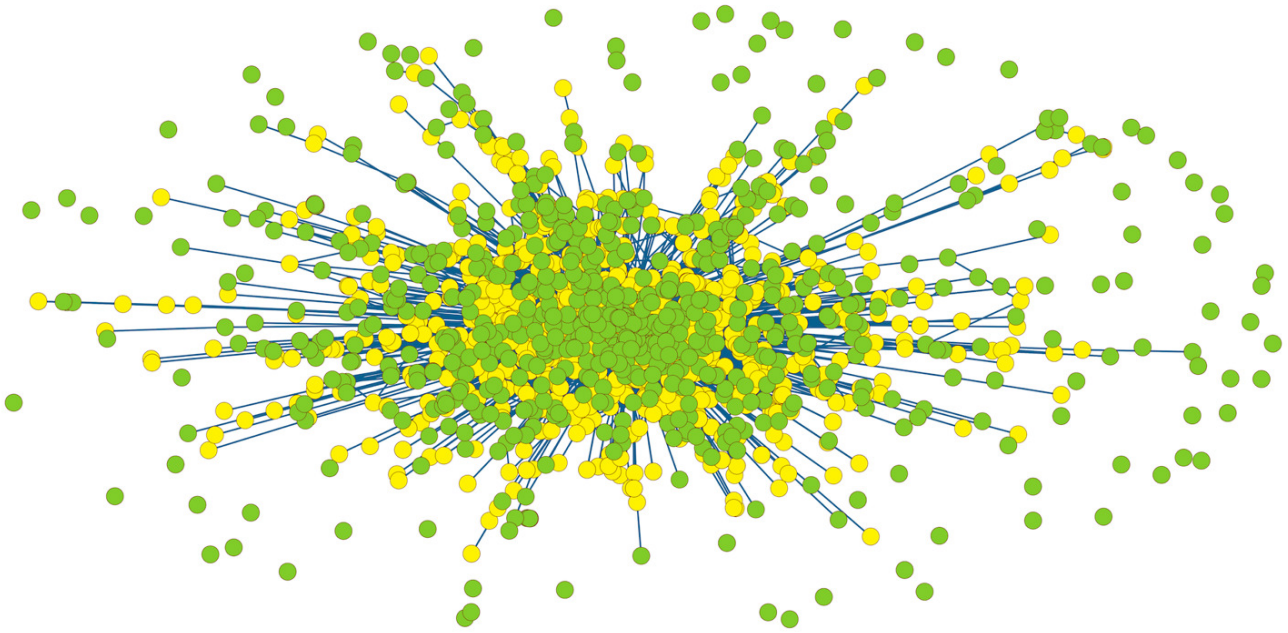
Figure 1. Energized full network using the Fruchterman-Reingold force-directed three-dimensional graph layout algorithm. Poets are represented in yellow, and composers in green. What appear as numerous green isolates are in reality green-yellow pairs: a poet and a composer who only work with each other, and thus are drawn very close together. This is clear in a video presentation (https://vimeo.com/874538881); as the structure turns, a node may switch from yellow to green or vice versa.

These visualizations indicate that while much of the network is connected in a single component, there are also many smaller components. While such visualization is important, it serves mainly to guide network analysis, especially for larger networks, whose visual representations are hard to read except in gross qualitative terms. The first step in that analysis is simply to count network elements.

We find 2,332 artists (nodes), including 1,593 poets (nodes in the first mode) and 739 composers (nodes in the second mode), linked by 5,834 collaborative relationships, of varying weights (each indicating the number of songs produced), summing to 12,523 collaborations (songs) in total. Already, network analysis has yielded an interesting fact (assuming that the dataset, even if not complete, is not biased): there are slightly more than twice[7] as many poets as composers involved in producing this collection of songs. This means that on average there are more than twice as many songs per composer as songs per poet, i.e. the average weighted degree for composers is more than twice the average weighted degree for poets. Further (since every collaboration links exactly one poet and one composer) there are more than twice as many collaborators per composer as collaborators per poet.

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7 Specifically, 1593/739 or approximately 2.16.

The average composer weighted degree is the total number of songs divided by the number of composers, and likewise for poets. On average poets participate in 7.86 song collaborations, as compared to 16.95 for composers, with an average of 3.66 collaborators, as compared to 7.89 for composers. These facts are not obvious from a simple song listing, but emerge instantly from a network representation.

If each collaboration requires approximately the same effort from poet and composer, this means composers are busier than poets in this world of song. Speculating, we may turn briefly to the interpretive phase. The disparity is perhaps understandable considering the high status of poetry in Arab society; poets may be writing on commissions outside the world of music (though composers may also be occupied with purely instrumental composition, this may be less common for song composers), and are perhaps more likely than composers to be amateurs involved in other non-poetry careers. Arab music composers tend to be more closely integrated in the music world, also serving as conductors and performers, and music is more likely to be a full-time occupation for them. This explanation is but an hypothesis, yet provides an instance of the interpretive act that must follow the purely analytical operations of social network analysis. It would be interesting to compare Arabic and Western popular music in this regard.

NETWORK COMPONENTS

Beyond such counting, it is useful to examine network connectivity. Recall that in a single component it is possible to walk from any node to any other, considering collaborations as links. Creative collaborations typically necessitate intensive social interactions, often requiring communications – messages are passed along these links. When a composer, say, collaborates with two different poets, messages may be passed between the two poets as well, via the composer as intermediary, and likewise for a poet working with two different composers. In other words, we can interpret a connected network as a social structure enabling messages to flow among its nodes, by means of links. Extra-network information helps confirm this possibility as most artists are Egyptian-born, and were alive in the mid-20th century. Conversely, we cannot make such an assertion for two artist-nodes each located in a different component, i.e. where there is no walk connecting them, even if communication is still possible in this case. A second analytical step, then, is to decompose the network into its disconnected pieces or components and conduct an inventory based on size.

The full bipartite network contains 2,332 nodes in 133 components. However, most nodes – 2,037 out of 2,332 or 87% – fall within a single large component, indicating great potential communicative connectivity among the vast majority of collaborating artists. Still, the network also contains 132 smaller components, ranging in size from two (dyadic collaborations) to seven. Of these, 113 (or 86%) are dyadic (size two). There are 12 instances of

size three (e.g. a poet who works with two different composers, none of them working with anyone else, or the reverse), four of size four, two of size five, and one of size seven.[8] In some cases these small components may result from missing data, which, if provided, would connect them to the large group. But the fact that most nodes are contained in a large 2,037 node component, such that a potential communicative path linking any two of them exists, is worthy of note, and calls for further analysis and interpretation.

SCALE-FREE DISTRIBUTIONS

One aspect of the collaboration network is typical of other networks (e.g. friendship) in large-scale urban environments: the scale-free distribution. Plotting any of degree (collaborators), weighted degree (collaborations), or link weights (strength of collaboration) as a histogram, we observe the "long tail" distribution. This distribution is typical of networks that form through so-called "preferential attachment": nodes with many neighbors tend to be preferred, and attract even more neighbors, because they are better connected; thus, "the rich get richer". This sort of distribution is called "scale free" because it contains no characteristic "scale"; mean and median do not represent a typical point on the distribution, unlike a normal (bell) curve, or the distribution of human height, for example. Scale-free distributions recur in many domains, from the distribution of wealth to the number of incoming links on websites.[9]

At the onset of any career, an artist has zero collaborations, though they may enjoy other network connections depending on the social environment into which they are born, including artist family members and friends. Some artists may be "better", in the sense of musical talent and quality, resourcefulness, versatility, dedication, or social appeal; others may simply be lucky. But once an artist attracts a critical mass of collaborators, they tend to accumulate more, perhaps roughly proportional to the number they already have, and the degree of these select individuals increases. By contrast, most artists collaborate with far fewer and mostly just one other person. (See Figures 2-4.)

C. The network's structural core

So far it has been difficult to view the network's structural core, defined by its strongest collaborations, as that core is hidden amidst so many low-degree nodes and low-weight links, representing weak collaborations. In order

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8 A component of size 1 is not possible since artists were only included in the dataset by virtue of having collaborated on at least one song; a component of size 6 is possible, but happens not to exist.

9 In music I have hypothesized that scale-free distributions characterize artist fame in the modern mediated era, when anyone can listen to any artist at any time. By contrast in premodern settings, with limited travel and no possibility of mediated performance, the distribution of artist fame should be closer to bell-shaped, with a concentration near the mean, because artists can only interact with proximate fans in live settings. Simulations support this hypothesis. (See Frishkopf, *Differentiating Traditional and Popular Music by Analyzing the Social Structure of Fame: A Computer Simulation of Fan - Artist Affiliations*)
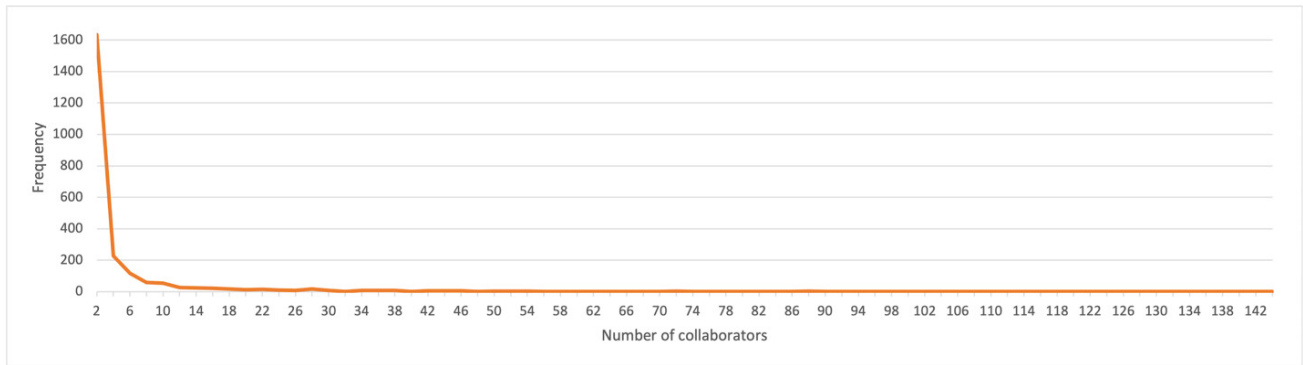
Figure 2. Histogram of degree (number of collaborators). The average is 5.0, maximum 142. The vast majority of artists have fewer than four collaborators, while very few have many. This curve resembles the expected power law of scale-free distributions (in contrast to a bell curve), and often results from a process of preferential attachment: artists with many collaborators tend to attract more, through the network itself.
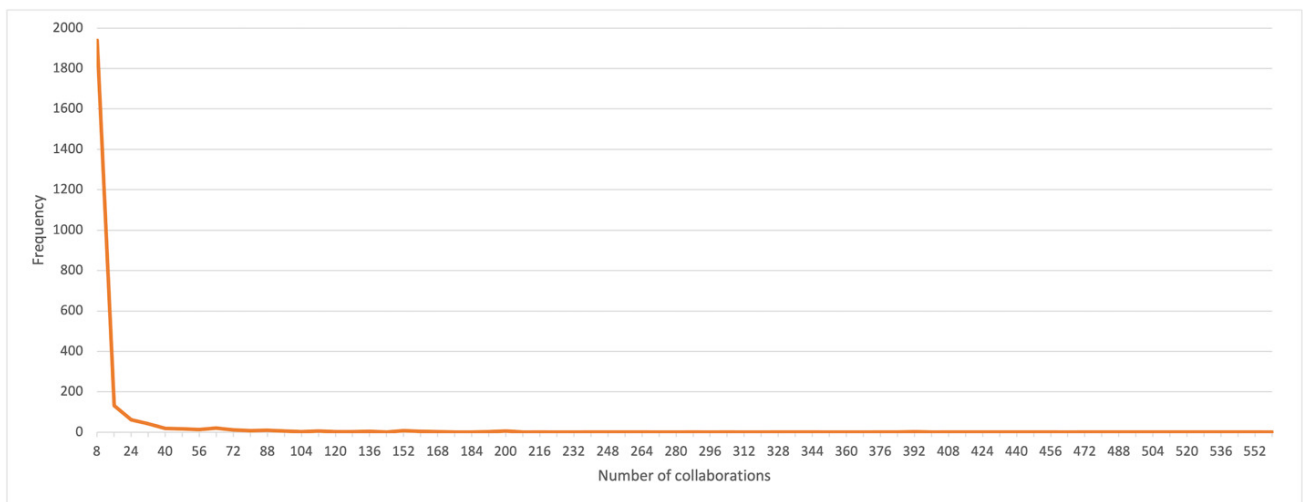

Figure 3. Histogram of weighted degree (number of collaborations). The average is 10.7, maximum 557. The same scale-free distribution appears as in Figure 2.
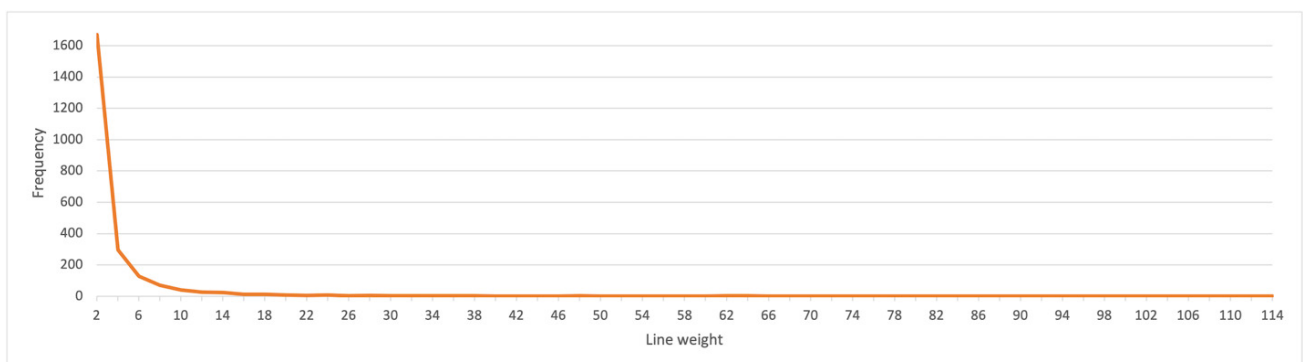
Figure 4. Histogram of line weights (strength of collaborations, i.e. number of songs). The average is 2.1, and the maximum is 114. Most collaborations are weakly productive (about 70% amount to just one song), while a few are extremely productive.

to view the core structure we need to peel away weak collaborations in order to see the stronger ones more clearly, via a threshold for significant collaboration. Such a threshold is bound to be somewhat arbitrary (one

of SNA's methodological problems is determining such cutoffs), but if we compute the 95th percentile of link weights (see [Figure 4](#)), we find that a minimum weight of 7 (i.e. collaborations on seven songs or more) represents the top 5% of all collaborations. Therefore, as a starting point we will define 7 songs as the threshold for "significant collaboration". We can then extract what is sometimes known as the "7-slice", comprising the subnetwork comprising lines of weight 7 or higher only. All weaker lines are deleted, along with any nodes that are thereby disconnected (i.e. which do not collaborate with anyone on at least seven songs). We can then re-energize this subnetwork in order to visualize its structure.

The 7-slice turns out to comprise 194 nodes: 113 poets, and 81 composers, connected by 274 links. It is noteworthy that the poet to composer ratio is lower within this more densely connected portion of the full network. Whereas the ratio for the full network was 2.16, for the strongly connected 7-slice, it is only 1.40. At the core of the network, the activity of composers and poets is closer to parity: collaborations per artist, and collaborators per artist, are more equal when comparing those poets and composers who are most active. Still there is a wide range in strength of collaborations. Link weights range from 7 to 114 songs, with an average weight of about 15.

There are 24 components, but only one of them is large, comprising 139 artists. The remainder comprise 19 poet-composer pairs (dyads), plus a handful of other relationships, with component sizes three, five, and six. I present the 7-slice and its components in [Figure 5](#).

Now that we've characterized the general structure of the 7-slice, we can zoom in on its large component, and begin to address two fundamental structural questions of social network analysis: Which artists are most central? And where are the network's cohesive subgroups?

CENTRALITY

Earlier I introduced five different centrality metrics: degree, weighted degree, closeness, betweenness, and eigenvector. Applied to the artist network, the first two evaluate centrality in terms of collaborators and collaborations, respectively, while the latter three consider the network as a structure that can support message-passing, identifying nodes that may play a key role in network communications.

Every node can be evaluated according to all five measures of centrality. As usual with SNA thresholds, the number of nodes to consider "central" is somewhat arbitrary; we want to limit this number to locate the core of the network, without reducing it too much, since the metrics themselves are also somewhat arbitrary (many other centrality metrics also exist). If we identify the dozen most central nodes in the large 7-slice component (139 nodes) for each of the five metrics, then in theory there could be as many as 60 central nodes,12 distinct nodes for each metric. (See [Table 2](#).)
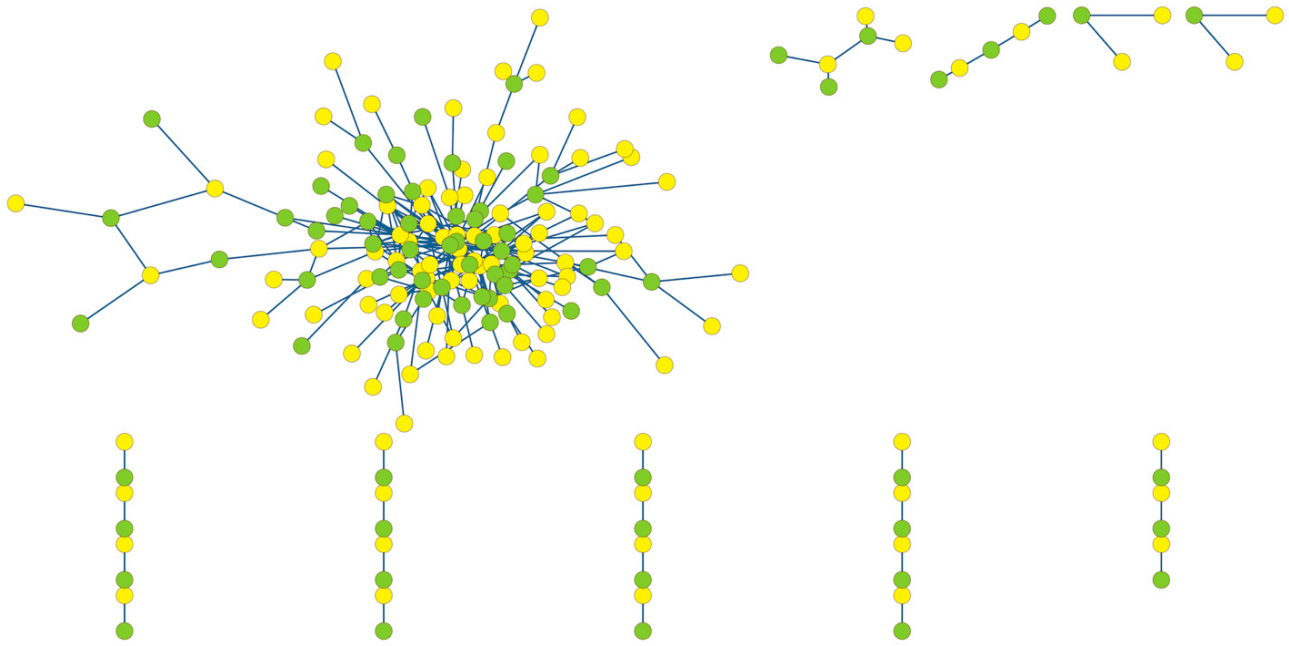
Figure 5. The 7-slice (energized using Kamada-Kawai) comprises 194 nodes, including a large component (139 nodes), 19 dyads (poet-composer pairs, at the bottom), and four other components of size 3, 5, and 6 (upper right). Again, poets are represented in yellow, and composers in green. The following videos energize using Fruchterman-Reingold in 3D: (a) the entire 7-slice: https://vimeo.com/874539449; (b) its large component: https://vimeo.com/874539464

Table 2. The dozen most central artists in the main component of the 7-core, ranked by degree centrality. P designates poet; C designates composer.

Rank	Name	Degree centrality	Role
1	Mohamed El Mougy	22	C
2	Abdel Fattah Mustafa	18	P
3	Abdel Azim Mohamed	15	C
4	Baligh Hamdi	14	C
5	Fathi Qura	13	P
6	Abdel Wahab Mohamed	12	P
7	Ahmed Sidqi	12	C
8	Riad Al Sunbati	11	C
9	Abdel Aziz Salam	10	P
10	Mohamed Ali Ahmed	10	P
11	Mohamed Abdel Wahab	10	C
12	Mahmoud al-Sharif	10	C

However, in practice there is heavy overlap among these five groups of 12, resulting in a total list of only 20 central nodes: 11 composers, and 9 poets. This is reassuring: it means that to a great extent the five centrality measures converge. We can summarize the situation by counting how often each node turns up in a top 12 list (ranging from 1 to all 5), and then ranking on this count. Adding birth and death dates as metadata helps in interpreting this data, suggesting a network of interacting contemporaries over several decades. (See Table 3 and Figure 6.)

Table 3. The top 20 most central artists, according to a combination of the five centrality metrics. All are Egyptian males. Several composers, such as Ahmed Sidqi, are rarely mentioned in music histories, but their centrality here emerges clearly. Note: ties are listed alphabetically.

| Rank	Name	# top 12 lists	Role
1	Abdel Azim Mohamed	5	C
2	Abdel Fattah Mustafa	5	P
3	Abdel Wahab Mohamed	5	P
4	Ahmed Sidqi	5	C
5	Baligh Hamdi	5	C
6	Mohamed El Mougy	5	C
7	Fathi Qura	4	P
8	Hussein Al-Sayed	4	P
9	Mohamed Abdel Wahab	4	C
10	Riad Al Sunbati	4	C
11	Mahmoud al-Sharif	3	C
12	Abdel Aziz Salam	2	P
13	Mohamed Ali Ahmed	2	P
14	Abdel Rahim Mansour	1	P
15	Abdel Rahman el-Abnudi	1	P
16	Helmy Amin	1	C
17	Hussein Junayd	1	C
18	Mohamed Fawzy	1	C
19	Mursi Gamil Aziz	1	P
20	Sayed Mekawy	1	C
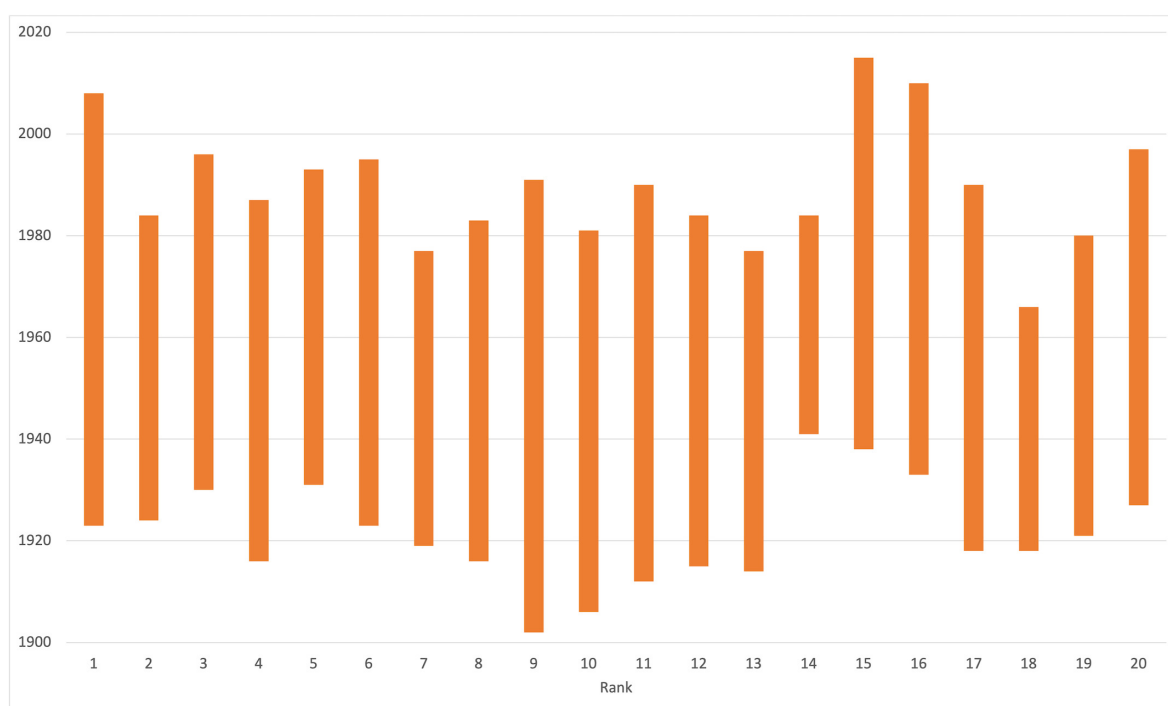
Figure 6. Lifespans of the top 20 most central artists, in rank order (see Table 3). Most are contemporaries from 1940 to 1980. As their lifespans overlap heavily, they likely participated in a productive and interactive musical community, catalyzed by the heyday of Egyptian Radio.

Table 4. The full network's seven most productive collaborations. Social network analysis greatly facilities detection of these relationships. Historical or cultural analysis can then attempt to explain them. Only three individuals (indicated with an asterisk) do not appear in the centrality list (Table 3).

Rank	Poet	Composer	Collaborations (link weight)
1	Hussein Al-Sayed	Mohamed Abdel Wahab	114
2	Abdel Fattah Mustafa	Ahmed Sidqi	66
3	Mursi Gamil Aziz	Mohamed El Mougy	63
4	Mohamed Hamza*	Baligh Hamdi	63
5	Abdel Rahim Mansour	Baligh Hamdi	62
6	Abdel Wahab Mohamed	Baligh Hamdi	62
7	Abdel Salam Amin*	Ammar El Sherei*	61

The number of composers and poets in the final centrality list are roughly equal. All are Egyptian and male, and the top six (four composers and two poets) are equally ranked, as are the following four (two poets, and two composers). From the metadata we observe that the lifespans of these most central 20 artists overlap heavily, meaning they could participate in a productive interwoven community. Of the top six composers, four (Baligh Hamdy, Mohamed El Mougy, Mohamed Abdel Wahab, and Riad al-Sunbati) are widely known in English-language music histories, but two others (Abdel Azim Mohamed and Ahmed Sidqi) are rarely mentioned. Why? While an historical inquiry beyond SNA is required in order to reveal the reasons, systematic network analysis has here proven its worth by revealing their importance and posing the question. As for poets, very few are discussed in English language sources, and identifying them constitutes an important contribution to Egyptian music history. Other questions are also raised. For instance, one may ask about the reasons for the the striking absence of central females as poets or composers, despite the large number of female singers. Is it due to a male bias in Egyptian radio holdings? Or due to broader social factors discouraging women from these roles? Network analysis doesn't provide all the answers, but can help to guide historical research in productive directions.

COHESION

Now let us consider cohesive subgroups (Wasserman and Faust, ch. 7). There are several ways to define these tightly connected groups of nodes. One may examine the most productive dyadic collaborations, or one may search for highly connected clusters. Link weight provides the former, while the latter may be revealed through several popular cluster detection algorithms, including (1) isolating components in higher K-slices (for K > 7); (2) detecting bipartite cliques, or (3) detecting communities.

Table 4 displays the most productive seven collaborations in the full network, representing the top 2.5% of all link weights. This list emerges immediately from network analysis, though it is hidden in the tabular data. While all the poets are different, one composer stands out as central to productive
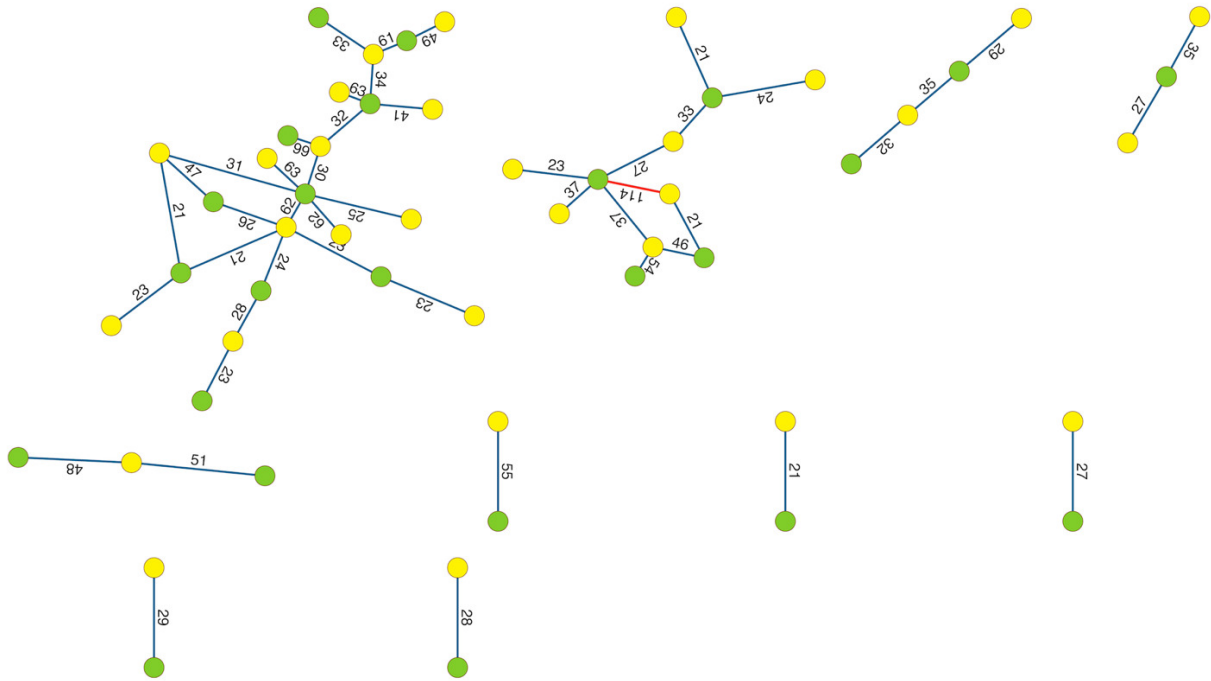
Figure 7. The 21-slice, with link weights indicated. The most productive collaboration (114 songs), between Mohamed Abdel Wahab and Hussein Al-Sayed, is highlighted in red. Historical or ethnographic research may explain why these particular groupings are salient.

collaborations: Baligh Hamdi, responsible for three of the links. There are 12 names altogether—seven poets and five composers—of which all but three (indicated with an asterisk) also appear on the centrality list (Table 3). Most striking is the collaboration between the famous composer Mohamed Abdel Wahab and poet Hussein Al-Sayed, with nearly twice as many collaborations as any other pair. Such an analysis once again demonstrates the power of SNA to highlight key figures and relationships, all of which can then be further explored and interpreted through more conventional qualitative historical or ethnographic research.

Honing in further on the most cohesive sections of the network, we can extract the 21-slice, and examine its components. Figure 7 indicates the structure, with link weights added. The structure thus revealed, other more qualitative methods of social science can be applied to explain them.

Another way to locate cohesive subgroups is to search for bipartite cliques. A clique is a fully connected subset of nodes. Thus a dyad is a clique of two, and a closed triad is a clique of three. A clique of four is a square with diagonals added. For two-mode (bipartite) networks, where links cannot connect within but only between modes, no cliques exist beyond the dyad. Therefore, a bipartite clique is defined as a subset in which every node in the first mode is connected to every node in the second; this subset is maximally connected within the bipartite network. For instance, Figure 8 represents a bipartite clique: four composers and four poets, with every possible poet-composer pair connected.
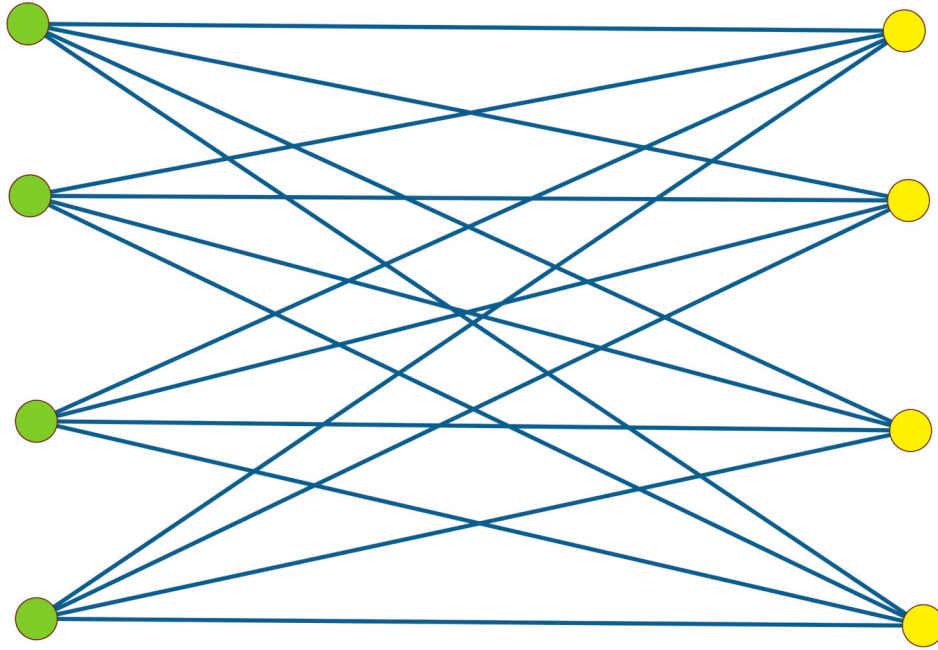
Figure 8. A bipartite clique on 8 nodes, 4 poets and 4 composers.

We can search for instances of such a structure throughout the larger network, counting the number of Figure 8-type cliques in which each network node is a member, in order to highlight cohesive subgroups. Searching detects three instances; the result is shown in Figure 9, where red nodes are members of all three cliques, green nodes are members of two, and yellow nodes are members of just one (nodes that are not members of any bipartite clique are removed). Energizing (using Kamada Kawai), the red nodes move to the center, and yellow nodes to the periphery. The analysis highlights the centrality of poet Abdel Fattah Mustafa and composer Mohamed El Mougy, who together link the two halves of this tightly connected web

Finally, we may also experiment with community detection algorithms, of which several are widely used. Informally, a community is a group of nodes that are densely connected to each other, but only sparsely connected to the rest of the network. We define a community partition as an assignment of every node to exactly one community (with this definition, communities do not overlap). The modularity of that assignment is defined as the fraction of all links that connect two nodes assigned to the same community (as opposed to connecting two nodes assigned to different communities), minus the expected such fraction in a random network with the same node degrees (since some links will fall within a single community even for a random network). Community detection algorithms attempt to assign nodes to communities such that modularity is maximized. In this way they help to reveal highly connected groups of nodes within the network.
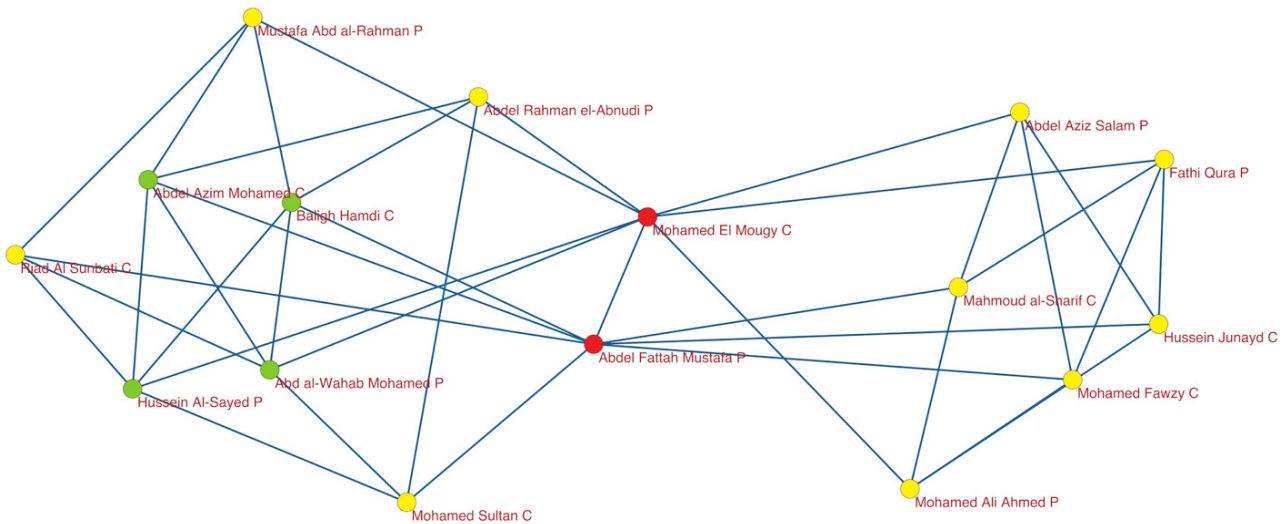
Figure 9. Searching for the bipartite clique illustrated in Figure 8, we find three instances. Here color does not indicate role. Rather, red nodes are members of all three instances, green nodes are members of two, and yellow nodes are members of just one. One poet and one composer (red nodes) play critical brokering roles, linking two halves of this network. (Poets are indicated with the suffix P; composers with C.)
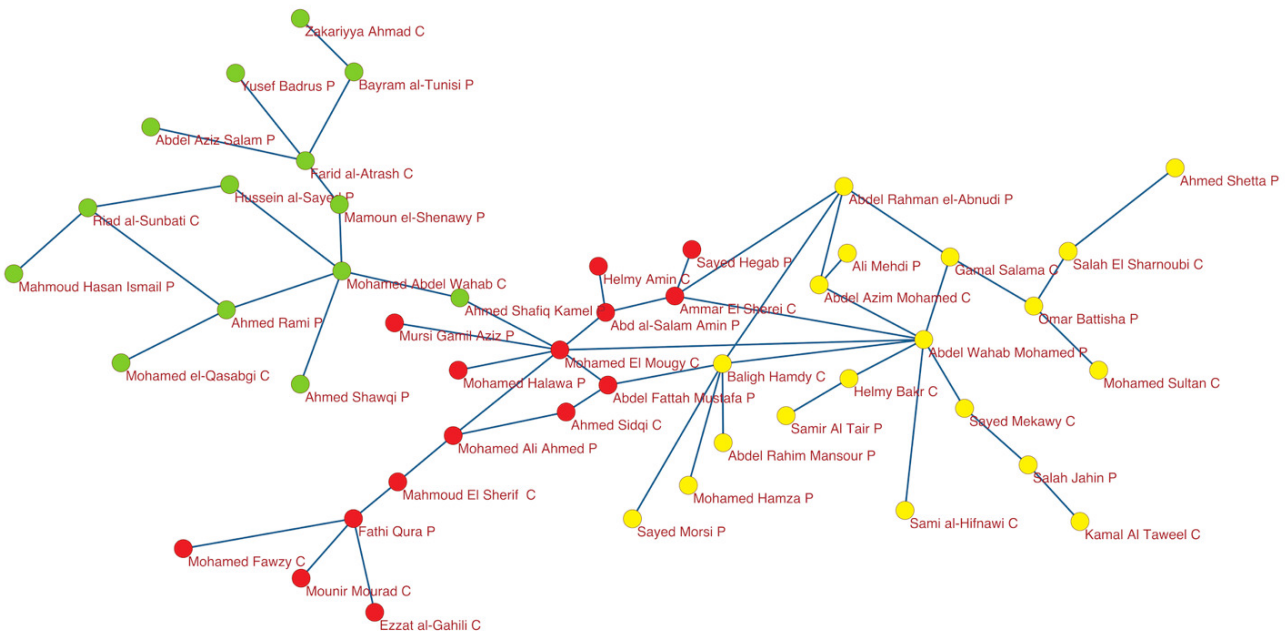

Figure 10. Results of Louvain community detection algorithm. To some extent these communities differentiate musical eras of the 20th century: early (green), mid (red), and later (yellow). But there also appear to be stylistic implications. (Poets are indicated with the suffix P; composers with C.)

Figure 10 shows the results of the Louvain community detection algorithm (Blondel et al.), applied to the large component of the 18-slice. Three communities have been circumscribed, with modularity 87%. Subsequent interpretation is required, based on metadata (such as date, or style), and contextual factors. To some extent these communities differentiate musical eras of the 20th century: early (green), mid (red), and later (yellow). But there also appear to be stylistic implications. More interpretive work is required.

III. Concluding remarks

Thus network analysis of a simple song database has highlighted important individuals, collaborative relationships, and cohesive subgroups, raising many important questions for further analysis and interpretation that would not otherwise even have been asked. I reiterate that social network analysis alone cannot answer many of the questions it raises. Rather, it is useful for drawing an empirically-grounded, big data, relational picture, and highlighting key features, structures, and relationships, to become focal points for subsequent historical or ethnographic inquiry. Applying social network analysis also means that the pitfalls of narrative histories – lack of big data, and lack of relational data – are avoided, because big relational data is required to perform social network analysis.

More practically, the application of social network analysis outlined in this article illustrates a general methodology for handling widely available collaboration data of this type, whether in music or any other domain, in three phases, which may be summarized as follows. First, gather and clean collaboration data, and assemble it as a network. Next, apply SNA to highlight features and relational structures that would otherwise remain invisible, such as lists of the most central nodes, the most important collaborations, or the most tightly connected subgroups. Finally, interpret these features and structures in light of broader socio-cultural and historical factors, in an attempt to explain why certain figures are central, or why certain subgroups are tightly connected. These interpretations may suggest further data-gathering and network analysis, forming a cycle of empirical research, network analysis, and interpretation.

In sum, the qualitative, critical interpretive methods of humanistic research and the quantitative, computational methods of social network analysis are not mutually exclusive, much less incompatible. Rather they blend harmoniously in music history, each complementing and guiding the other. If the methodological balance formerly tilted toward the former, perhaps the recent availability of big data and SNA tools, along with greater acceptance of digital humanities among music scholars, will help restore equilibrium, enriching our understanding of music history in the process.

Data repository: https://doi.org/10.7910/DVN/8QYNVS

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