Community structures and role detection in music networks

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We analyze the existence of community structures in two different social networks using data obtained from similarity and collaborative features between musical artists. Our analysis reveals some characteristic organizational patterns and provides information about the driving forces behind the growth of the networks. In the similarity network, we find a strong correlation between clusters of artists and musical genres. On the other hand, the collaboration network shows two different kinds of communities: rather small structures related to music bands and geographic zones, and much bigger communities built upon collaborative clusters with a high number of participants related through the period the artists were active. Finally, we detect the leading artists inside their corresponding communities and analyze their roles in the network by looking at a few topological properties of the nodes. © *2008 American Institute of Physics*.
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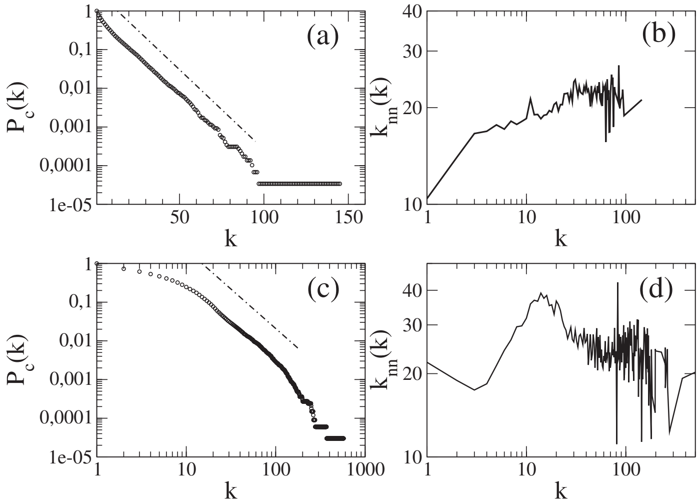
Music is one of the richest sources of interaction between individuals. Besides the usual connections between artists and listeners, it is possible to have artist-artist and listener-listener relations. In the current work we analyze artist-artist interactions and their implications in music similarity and collaboration. To that end, we construct two different networks where nodes represent musical artists: the similarity network, where artists are linked if a certain similarity exists between them (evaluated by musical editors), and the collaboration network, where a link exists between two artists if they have ever performed together. We detect and analyze the internal communities that spontaneously arise in both networks, which are driven by musical/social "forces," and show that the appearance of these communities is strongly related to the existence of musical genres. Furthermore, we are able to discriminate the main actors in the formed structures and extract their role in the network through the calculation and classification of a few topological properties of the nodes.

I. INTRODUCTION

Since the seminal paper of Milgram[1] investigating the flow of information through acquaintance networks, social (complex) networks have attracted the interest of scientists in a variety of fields.[2] Many kinds of social structures arise when analyzing the different types of interdependency among individuals (or organizations), such as financial exchange, friendship, kinship, sexual relations, or disease transmission. In the current work we focus on those social networks where music is the driving force that generates interaction between individuals. Specifically, we consider musical artists as the fundamental nodes of the network and a certain musical relation as the linking rule. Two different types of networks are obtained: first, the similarity network, where artists are linked if their music are somewhat similar, and second, the collaboration network, where artists are linked if they have ever performed together. The relevance of these kinds of networks does not only rely on a social science perspective but also in musical aspects, such as the understanding of musical genres[3,4] or music recommendation.[5]

Networks are obtained from the All-Music database of music metadata.[6] The content of the database is created by professional editors and writers. Despite the linking rule being clear when creating the collaboration network, the similarity between artists is a more complex task. A great deal of research is devoted towards the development of audio content-based algorithms capable of quantifying similarity between musical pieces.[7–9] Although great advances have been made in this field, the criterion of musical experts still prevails over similarity software. If we translate the problem from musical pieces to musical artists,[10] the evaluation of musical similarity becomes a subjective task where expert musical editors have the last say.

The intersection between both networks has been recently analyzed[11] from a complex network perspective.[12,13] In the current work we go one step further by studying the structures that arise in the spontaneous organization of these particular social networks. Specifically, we are interested in the existence and characterization of communities inside the network and the driving forces that induce their appearance. We also see how different kinds of community structures arise at different partition levels and how they are related to the existence of musical genres (in the case of the similarity network) and inter/intra-band collaboration (in the case of the collaboration network). Figure 1 summarizes the main parameters of the network together with the cumulative de-



	Similarity	Collabor.
n	29203	33246
m	118941	127020
k_{max}	145	574
D	22	23
<d> $<d>_{random}$	6.233 (5.713)	6.077 (5.353)
C C_{random}	0.202 (0.00025)	0.348 (0.00024)
r	0.1291	-0.0299

FIG. 1. [(a) and (c)] The cumulative degree distribution $P_c(k)$ of the similarity and collaboration networks respectively (note the different scale in the X axis). [(b) and (d)] Their corresponding nearest neighbor degree distributions $k_{nn}(k)$. Parameters shown in the table are: number of nodes (n), number of links (m), highest degree ($k_{\max}$), diameter of the network (D), mean shortest path ($\langle d\rangle$), clustering coefficient (C), and Pearson correlation coefficient (r) (see Ref. 15).

gree distributions $P_c(k)$ and the nearest neighbor degree distributions $k_{nn}(k)$. Despite both networks sharing a small world topology,[14] there exist differences in their degree distribution and assortativity.[11,15]

II. COMMUNITY DETECTION

Detection of communities in complex networks has gained a lot of attention during recent years,[16–18] a fact reflected in the existence of several community-detection algorithms. Among them, we have selected the Girvan–Newman (GN) algorithm[19] for its agreement between effectiveness and time consumption. As we will explain later, the GN is valid only for low to moderate values of the inter-community connections, which is the case of the networks analyzed here.

The GN algorithm is based on the sequential removal of those links with the highest betweenness, which is measured as proportional to the number of shortest paths running along each link.[19] This way, the network breaks into isolated clusters (communities) which, in turn, can be further split in successive steps. In Fig. 2, we plot this evolution for the similarity network. In order to understand the emergent communities, we use the fact that the All Music database tags each artist as belonging to one or more genres and we choose the most frequent tag to label each community. We can identify the first split as a hip-hop community, followed by the division into two main groups dominated by "rock" and "jazz" artists, respectively. In subsequent divisions there appear genres such as Blues, Opera, or Hard Rock from the former "rock" community, and Jazz, Latin-Bolero, and Standards from the Jazz community.

In order to quantify the quality of the divisions we compute the modularity Q of each partition. As explained in Ref. 19, a modularity $Q=0$ indicates that the detected community structure is similar to the one existing in an equivalent random network or, in other words, links between nodes are randomly distributed and they are not related to the existence

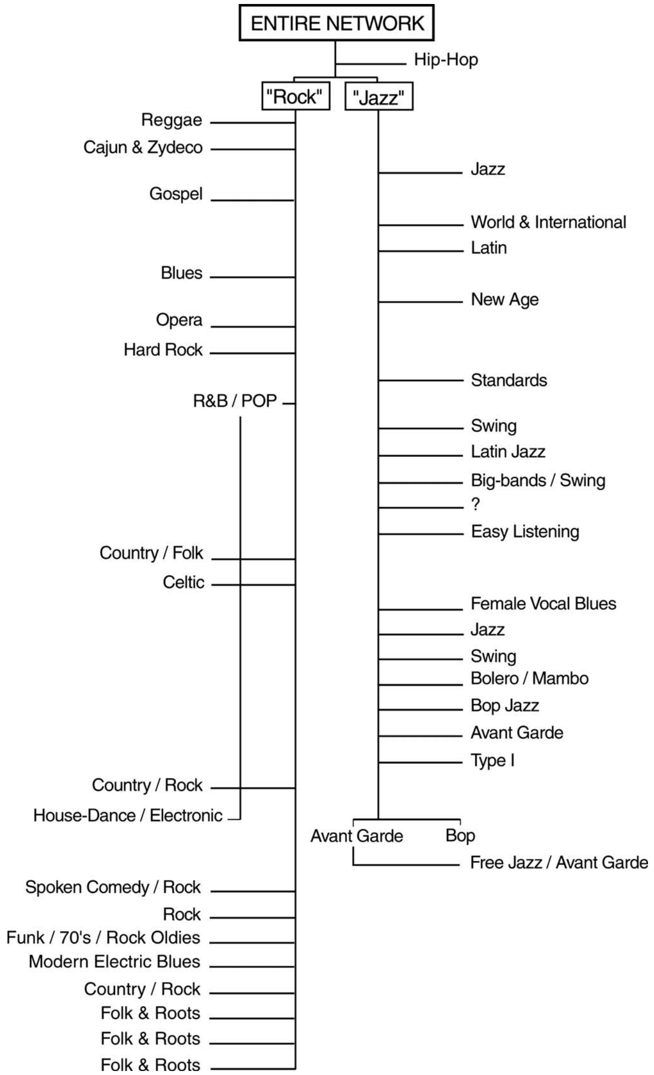


FIG. 2. Dendogram of communities detected in the similarity network when applying the GN algorithm. In every step (left column) a cluster (community) splits out from the network.

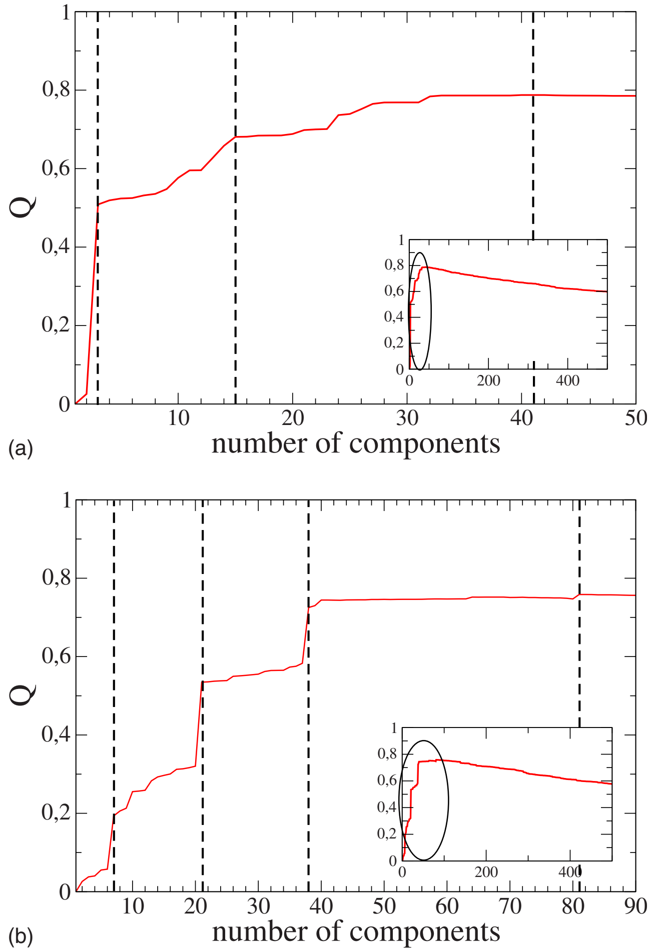


FIG. 3. (Color online) Modularity Q of the communities (insets) as the GN algorithm splits the similarity (a) and collaboration (b) networks. In the main plots, we have zoomed in on the region indicated in the insets, which correspond to the maximum of the Q evolution. Dashed lines indicate sudden increments of Q.

of certain cliques inside the network. On the contrary, values approaching $Q=1$, which is the maximum, indicate strong community structure.

Figure 3 shows the evolution of the modularity (Q) (Ref. 19) as both networks are divided into independent clusters (by the removal of links with the highest betweenness). We can observe the existence of sudden increments of Q related to different satisfactory network partitions. As reported in Ref. 19, the absolute maximum is not always associated with the best partition, and therefore, each of these large jumps in Q must be analyzed independently with regard to the nature of the data.

As we saw in the dendogram of the similarity network (Fig. 2), the possible partitions are related to the genre classification of the artists belonging to each detected community. The maximum value of Q ($Q \simeq 0.79$) appears when the network is split into 41 communities, all of them related to musical genres or styles within those genres. However, the most significant partition is observed when the network is divided into 15 communities ($Q \simeq 0.68$) since each community can easily be described by a well defined musical genre. Further divisions of this network are dominated mainly by the appearance of different styles inside each genre.

In the case of the collaboration network, the maximum appears for 81 communities with a $Q=0.76$. In this case, the interpretation of the existing communities is more complex since several factors such as generational overlapping, geographical proximity, genre affinity, or, simply, the existence of music bands, induce community formation.

It is worth mentioning that the obtained values of modularity reveal a strong community structure. In all the mentioned cases the percentage of inter-community links were always less than 17%. If we compare with toy-networks used to evaluate community detection algorithms,[18] we see that these values of inter-community links correspond to the region where the GN algorithm is as good as the others. This conclusion is also supported if we look at the inset of Fig. 3 in Ref. 20, where the authors show that values of modularity Q greater than 0.5 correspond to a region where the GN algorithm performs accurately. All this evidence supports the use of the GN algorithm as a suitable community detector in these kinds of networks.

In Fig. 4 we plot the most significant partitions detected by the community structure algorithm, i.e., a division into 15 communities in the case of the similarity network (left plot) and 41 communities in the collaboration network (right plot). Since each cluster of the similarity network is related to a certain musical genre, we assign different colors to each community and we keep them in the collaboration clusters. This way, we can observe how musical genres spread among the collaboration clusters and we can compare the relation between genres and collaborations. Concerning the collaboration network, two kinds of communities are detected, one with a small number of nodes corresponding to the existence of bands and geographic zones, and the other related to certain collaboration communities, where jazz artists are the most interactive nodes. It is remarkable that two of the largest collaboration communities (3 and 5) are formed mainly by jazz players, a community of artists that presents a high degree of collaboration. We identify two kinds of "collaborators" in these big communities: one related to artists who usually play in several bands during their career (e.g., John Coltrane or Stan Getz) and the other related to jazz artists that usually perform as sessionists given that they are experts in one particular instrument (e.g., Paulinho Da Costa or Ron Carter). Furthermore, these two largest communities correspond to different generations of jazz players, community 3 to the 1920s–1930s–1940s and community 5 to the 1950s–1960s. Interestingly, the community of jazz artists who performed together between 1912 and 1940 (which would correspond to community 3 of Fig. 4) was previously studied in Ref. 21.

III. ROLE CLASSIFICATION

Once the existing communities have been identified, we will try to infer the artists' roles inside their communities by mere inspection of the network topology. Recently, Guimerà *et al.*[22] have introduced a classification of the node functionality by analyzing the connectivity of nodes within the community structure. Two properties of the node connectivity based on the inter/intra-community connections are checked.

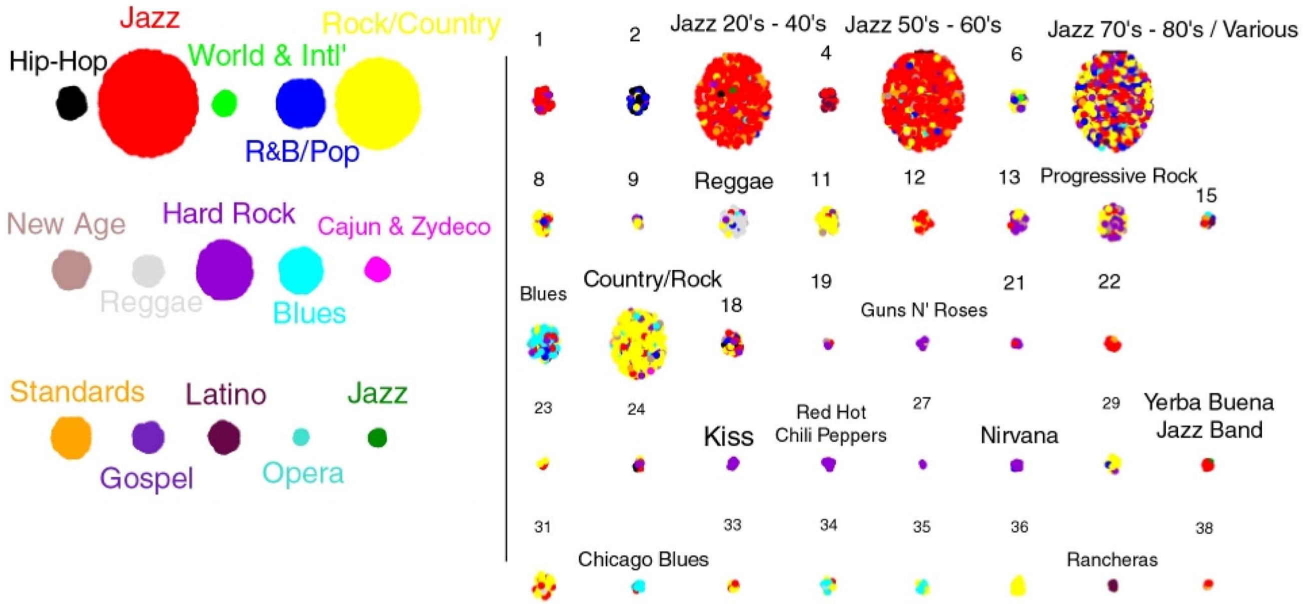


FIG. 4. (Color online) Detected communities for the similarity (left) and collaboration (right) networks. Different shades of gray (see also the color online figure), which correspond to different musical genres (similarity communities), are introduced to help comparison between similarity and collaboration communities.

One is the within-module degree z_i, which accounts for the connections of the node inside its community, and is defined as

$$z_i = \frac{\kappa_i - \bar{\kappa}_{s_i}}{\sigma_{\kappa_{s_i}}}, \qquad (1)$$

where κ_i is the degree of node i, $\bar{\kappa}_{s_i}$ is the mean degree inside the community s_i of node i, and $\sigma_{\kappa_{s_i}}$ is the standard deviation of k in s_i. High values of z_i reflect that node i is a well connected node inside its community (i.e., a hub), while negative values indicate a connectivity below the average (peripheral nodes).

Another characteristic to be evaluated is how the links of a certain node are distributed between the communities. This is measured using the participation coefficient P_i and accounts for the inter-community link distribution of node i,

$$P_i = 1 - \sum_{s=1}^{N_M} \left(\frac{\kappa_{is}}{\kappa_i} \right)^2, \qquad (2)$$

where N_M is the total number of communities, κ_{is} is the number of links of node i that are connected to nodes in community s, and κ_i is the total degree of node i. The participation coefficient ranges from zero (all links inside its own community) to close to unity (all links equally distributed among all communities).

In the role classification proposed by Guimerà *et al.* the functionality is obtained by analyzing the position of nodes in a two-dimensional space given by (P_i, z_i). Nodes with $z \geqslant 2.5$ are considered hubs and $z < 2.5$ are nonhubs. The two-dimensional space representation is divided into seven regions: four of them for nonhub nodes: (R1) ultra-peripheral nodes, i.e., nodes with few connections which belong, in turn, to a unique community; (R2) peripheral nodes, which are nodes with few links outside their community; (R3) nonhub connector nodes, i.e., nodes with several connections to other communities; and (R4) nonhub kinless nodes, with their links homogeneously distributed among all communi-

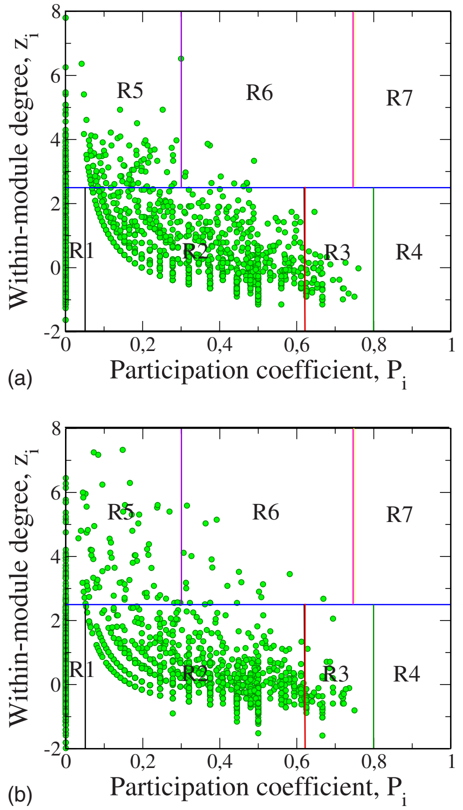


FIG. 5. (Color online) Position of nodes in two-dimensional space (P_i, z_i) for the similarity network (a) and the collaboration network (b). Seven divisions of the two-dimensional space used to classify nodes roles are shown explicitly.

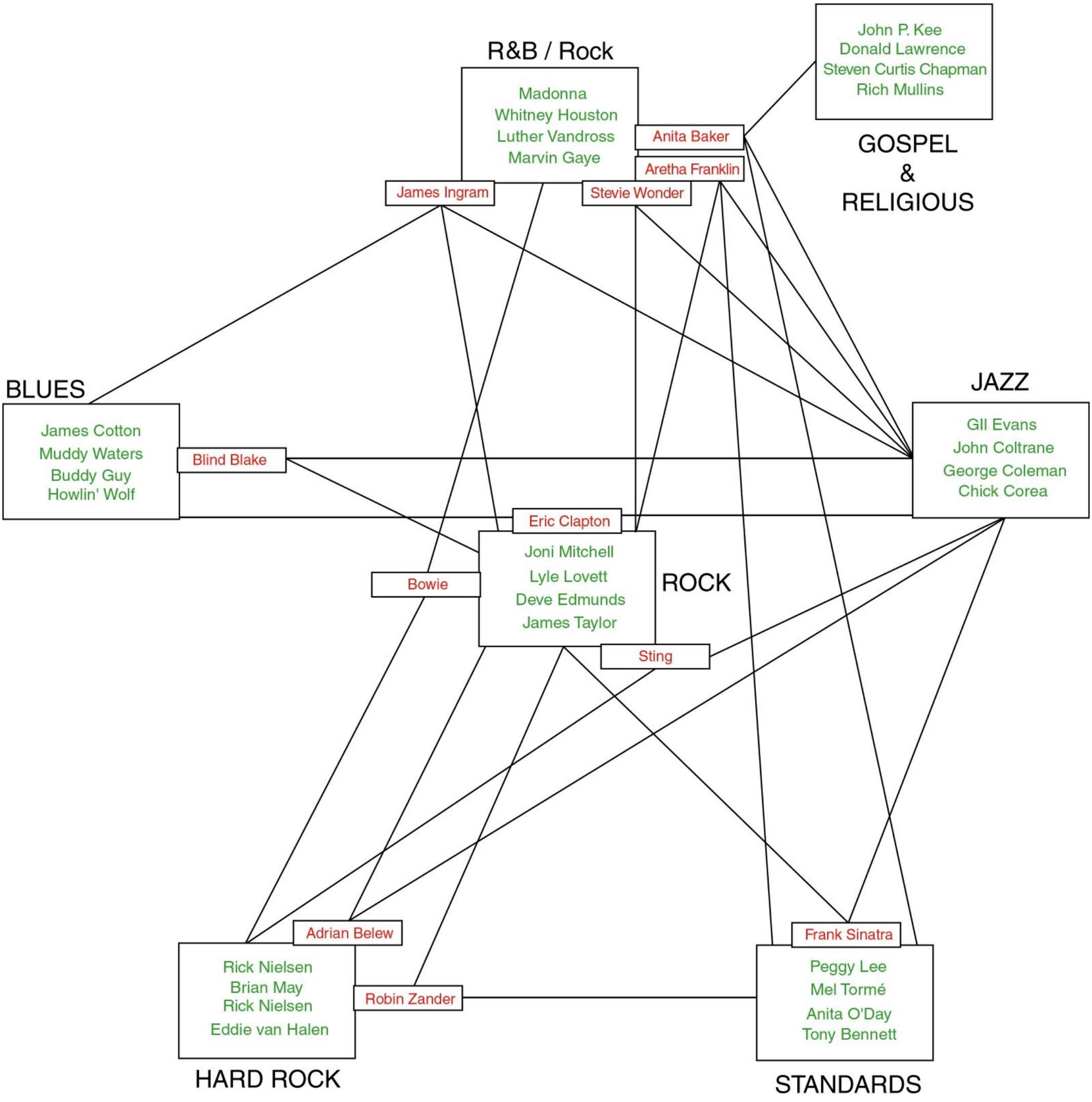


FIG. 6. (Color online) Cartographic representation of the similarity communities. Due to space limits, only the seven largest communities have been plotted. Provincial hubs (R5, green/large boxes) and connector hubs (R6, red/small boxes) have been indicated, in order to show leading artists inside each community and also those artists that act as bridges between musical genres.

ties. The other three regions divide the types of hubs into (R5) provincial hubs, i.e., hubs with a large number of their links inside their community; (R6) connector hubs, which distribute around 50% of their links in several communities; and (R7) kinless hubs, whose links are homogeneously distributed among all communities.

In our particular case, we use this classification (after ensuring that it works correctly in our network) in order to identify the central nodes of each community, i.e., the most influencing artists within a particular musical genre, and also those artists who, due to their versatility, link two or more musical genres.

Figure 5 shows the position of nodes in the two-dimensional space (P_i, z_i) for both networks. Provincial hubs of the similarity network (R5) are references in their musical genres. In this category, we find artists such as Elvis Presley, Elton John, Bruce Springsteen, The Rolling Stones, Whitney Houston, Madonna, Joe Satriani, Axl Rose, John Coltrane, and Gil Evans. On the other hand, there exist artists who are references in their communities but they also stood out for having performed in two or more genres. These artists belong to the R6 category (connector hubs) and we find names as Stevie Wonder, Eric Clapton, Aretha Franklin, Anita

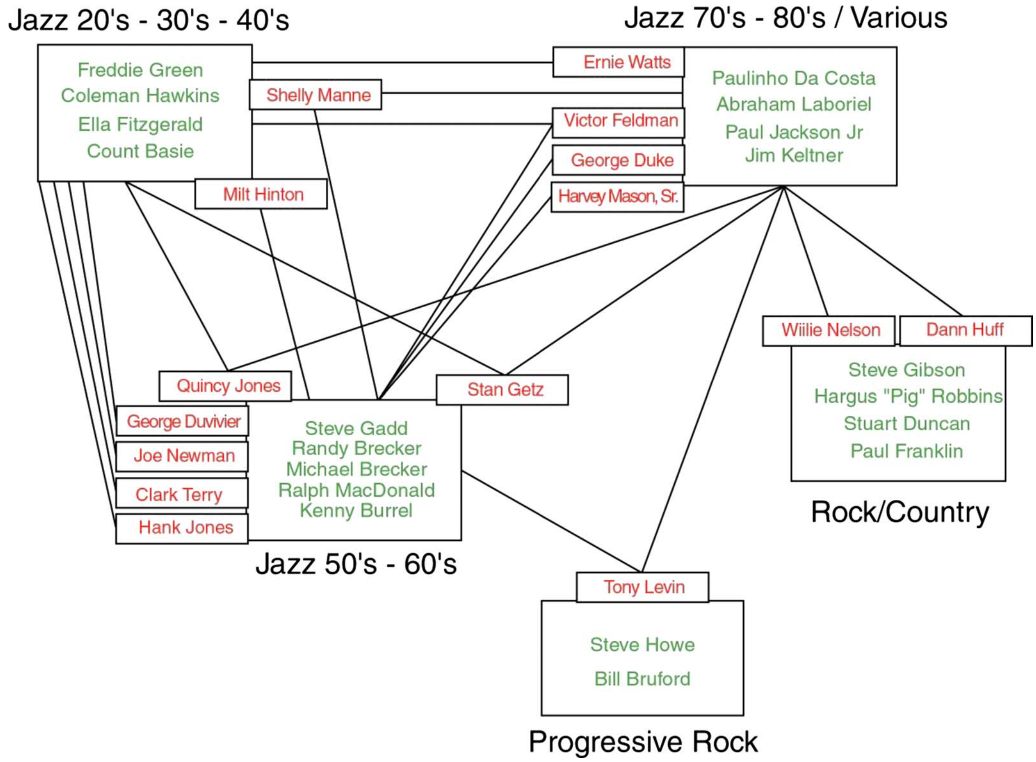


FIG. 7. (Color online) Cartographic representation of the collaboration clusters. Due to space limits, only the five largest communities have been plotted. Provincial hubs (R5, green/large boxes) and connector hubs (R6, red/small boxes) have been indicated, in order to show leading artists inside each community and also those artists that act as bridges between collaboration clusters.

Baker, James Ingram, Sting, David Bowie, Frank Sinatra, Vangelis, Blind Blake, Robin Zander, and Adrian Belew.

In Figs. 6 and 7 we plot a cartographic representation of the seven largest communities within the similarity network (Fig. 6) and the five largest ones in the collaboration network (Fig. 7), where provincial (R5) and connector (R6) hubs have been explicitly indicated (the rest have been omitted in order to ease the reading). This representation allows us to identify not only the artists who are references of each musical genre or collaboration clique, but also those who act as bridges between communities.

As an example, within the Rock community we can observe how Eric Clapton is a connector hub that links the Rock genre with the Blues and Jazz communities. Therefore, Eric Clapton is an internal connector of the Rock community. Other kind of connector hub is Blind Blake, who belongs to the Blues cluster. This artist is an external connector of the Rock community, since it is one of the bridges between the Blues and Rock communities. This type of representation provides an objective mechanism for classifying the function of leader artists inside their musical communities by using topological properties of the network and furthermore to quantify connections between different musical genres.

IV. CONCLUSIONS

We have shown that the identification of community structures within music networks is a useful tool in order to evaluate the existence of musical cliques and to identify the role of leading artists inside each community. In the case of music similarity networks we have observed that the detected communities are related mainly to musical genres, while the collaboration network presents communities related to artists generations, geographical constraints, genre affinity, or music bands. In the collaboration network, for example, jazz players are the most active artists and give rise to the appearance of large communities related to different generations. Finally, we have studied a method to identify the leading artists of each community and the internal/external connector hubs, who act as bridges between different musical genres. The information obtained from the community analysis could be a useful tool not only to evaluate the role or relevance of a given artist but to improve the performance of music recommendation systems.[23,5,24]

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