

Uncovering collective listening habits and music genres in bipartite networks

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In this paper, we analyze web-downloaded data on people sharing their music library, that we use as their individual musical signatures. The system is represented by a bipartite network, nodes being the music groups and the listeners. Music groups' audience size behaves like a power law, but the individual music library size is an exponential with deviations at small values. In order to extract structures from the network, we focus on correlation matrices, that we filter by removing the least correlated links. This percolation idea-based method reveals the emergence of social communities and music genres, that are visualized by a branching representation. Evidence of collective listening habits that do not fit the neat usual genres defined by the music industry indicates an alternative way of classifying listeners and music groups. The structure of the network is also studied by a more refined method, based upon a random walk exploration of its properties. Finally, a personal identification–community imitation model for growing bipartite networks is outlined, following Potts ingredients. Simulation results do reproduce quite well the empirical data.

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I. INTRODUCTION

Answering a common question such as “What kind of music do you listen to?” is not an easy task and is full of hidden information about oneself. Indeed, music is omnipresent in our society and is part of everyday life. Moreover, it is well known in social sciences [1] that music does not function merely as entertainment, but is deeply related to identity building and community building. In that sense, personal musical choices derive from a subtle interplay between cultural framework inheritance, social recognition, and personality identification. These reinforce one's self-image and send messages to others [2]. Due to the complexity of taste formation and the richness of available music, it is tempting to postulate that someone's music library is a unique signature of himself [3]. For instance, it is interesting to point to the empirical study by D'Arcangelo [4] which shows that listeners strongly identify with their musical choice, some even going so far as to equate their music collection with their personality: *My personality goes in my iPod*, as an interviewed person claims. Consequently, it is difficult for people to recognize themselves in usual music divisions, such as punkers versus metal heads, or jazz versus pop listeners. And, more commonly, they answer to the above question “Everything... a little bit of everything.”

Recently attempts have been made to characterize the musical behavior of individuals and groups using methods from quantitative sociology and social network analysis. These attempts were made possible because of the huge amount of music databases available now, associated with the current transition from materialized music (LP's, CD's, etc.) to computer-based listening habits (iTunes, iPod, etc.). Among other studies, let us cite the recent empirical work by Volda *et al.* [5], which shows that people form judgements about

colleagues based on the taste—or lack of taste—revealed by their music collection, and admit to tailoring their own music library to project a particular person.

The present paper focuses on these musical behaviors from a statistical physics and statistical point of view, by analyzing individual musical signatures and extracting collective trends. This issue is part of the intense ongoing physicist research activity on opinion formation [6–10], itself related to phase transitions and self-organization on networks [11,12], including clique formation [13]. The characteristics of such phenomena depend on the type of network, as well as on the data size, thereby questioning universality, in contrast with statistical mechanics.

In Sec. II, we extract empirical data from collaborative filtering websites, e.g., *audioscrobbler.com* and *musicmobs.com*. These sites possess huge databases, that characterize the listening habits of their users, and allow these users to discover new music. Our analysis consists in applying methods from complex network theory [14] in order to characterize the musical signatures of a large number of individuals. In Sec. III, we present original percolation idea-based (PIB) methods in order to visualize the collective behaviors. They consist in projecting the bipartite network, where listeners and music groups are linked, onto a unipartite network, i.e., a network where listeners are connected depending on the correlations between their music tastes. Let us stress that the usual projection method ([15], see details below), used in co-authorship networks, for instance, does not apply in the networks hereby considered, as it leads to almost fully connected networks. In this work, we also project the bipartite network on a network of music groups, and probe the reality of the usual music divisions, e.g., rock, alternative and punk, classical. We propose a quantitative way to define more refined musical sub-divisions. These subdivisions, that are not based upon usual standards but rather upon the intrinsic structure of the audience, may lead to the usual music genres in some particular case, but also reveal unexpected collective listening habits. Let us note that other techniques may also lead to an objective classification of music, e.g., by charac-

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terizing their time correlation properties [16]. In general, the identification of *a priori* unknown collective behaviors is a difficult task [17], and of primordial importance in the structural and functional properties of various networked systems, e.g., proteins [18], industrial sectors [19], groups of people [20], etc. Consequently, we also use another method in Sec. IV in order to uncover these structures, i.e., the percolated island structure is explored by randomly walking (RW) the network, and by studying the properties of the RW with standard statistical tools. Finally, in Sec. V, we present a growing network model, whose ingredients are very general, i.e., personal identification and community imitation (PICI). The model reproduces the observed degree (number of links per node) distributions of the networks as well as its internal correlations.

II. METHODOLOGY

Recently new kinds of websites have been dedicated to the sharing of musical habits. These sites allow first members to upload their music libraries, previously stocked on their computers, towards a central server, and next to create a web page containing this list of music groups. Additionally, the website proposes the users to discover new music by comparing their taste with that of other users. These methods of making automatic predictions for the interests of a user by collecting information from many (collaborating) users is usually called *collaborative filtering* [21]. The data that we analyze here have been downloaded from *audioscrobbler.com* in January 2005. It consists of a listing of users (each represented by a number), together with the list of music groups the users own in their library. This structure directly leads to a bipartite network for the whole system. Namely, it is a network composed by two kinds of nodes, i.e., the persons, called users or listeners in the following, and the music groups. The network can be represented by a graph with edges running between a group i and a user μ , if μ owns i .

In the original data set, there are 617 900 different music groups, although this value is skewed due to multiple (even erroneous) ways for a user to characterize an artist (e.g., *Mozart*, *Wolfgang Amadeus Mozart*, and *Wolfgang Amadeus Mozart* count as three music groups) and 35 916 users. There are 5 028 580 links in the bipartite graph, meaning that, on average, each user owns 140 music groups in his/her library, while each group is owned by eight persons. For completeness, let us note that the listener with the most groups possesses 4072 groups (0.6% of the total music library) while the group with the largest audience, *Radiohead*, has 10 194 users (28% of the user community). This asymmetry in the bipartite network is expected as users have in general specific tastes that prevent them from listening to any kind of music, while there exist *mainstream* groups that are listened to by a very large audience. This asymmetry is also observable in the degree distributions for the people and for the groups. The former distribution (see Fig. 1) is fitted respectively with an exponential $e^{-n/150}$ for large n and the latter is a power law $n^{-1.8}$, where n is the number of links per node, i.e., n_G or n_L for groups and listeners, respectively. Let us stress that such distributions are common in complex net-

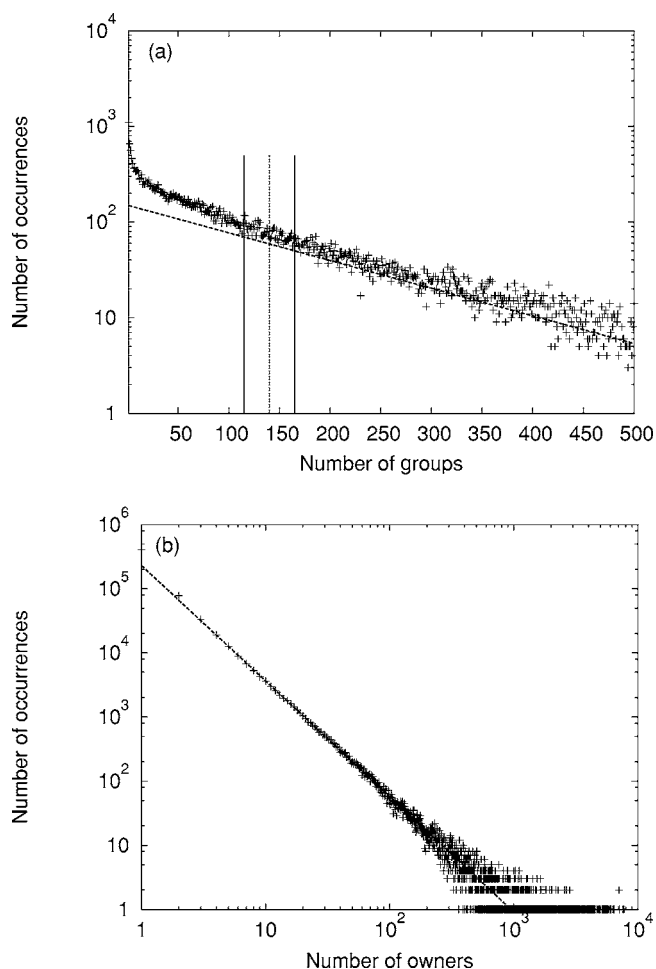


FIG. 1. (a) Histogram of the number of music groups per user. The tail is fitted with the exponential $e^{-n/150}$ (dashed line), where n is the number of links per node. A specific interval examined in the text is indicated by vertical lines: average $\langle n_G \rangle = 140$, width 50; (b) Histogram for the audience size (number of listeners) per music group. This distribution behaves like the power law $\sim n_L^{-1.8}$.

works [14]. For instance, co-authorship networks also exhibit a bipartite asymmetry, and power law distribution $n^{-\alpha}$, with $\alpha \sim 2$ [22].

Finally, let us mention the top ten groups in hierarchical order: *Radiohead*, *Nirvana*, *ColdPlay*, *Metallica*, *The Beatles*, *Red Hot Chili Peppers*, *Pink Floyd*, *Green Day*, *Weezer*, and *Linkin Park*. Obviously, the examined sample is oriented toward recent *rock* music. This fact has to be kept in mind, as it determines the mainstream music trend in the present sample, and could be a constraint on expected universality. This is left for further studies.

A common way to represent and to study bipartite networks consists in projecting them onto links of one kind [15]. The standard projection method simplifies the system to a unipartite network, where nodes are, e.g., the listeners and where two listeners are connected if they have at least one music group in common. This scheme, that leads to a helpful representation in the case of collaboration networks [23,24], is unfortunately meaningless in the case under study. Indeed, due to the existence of mainstream music groups, the unipartite network is almost fully connected, i.e., most of the lis-

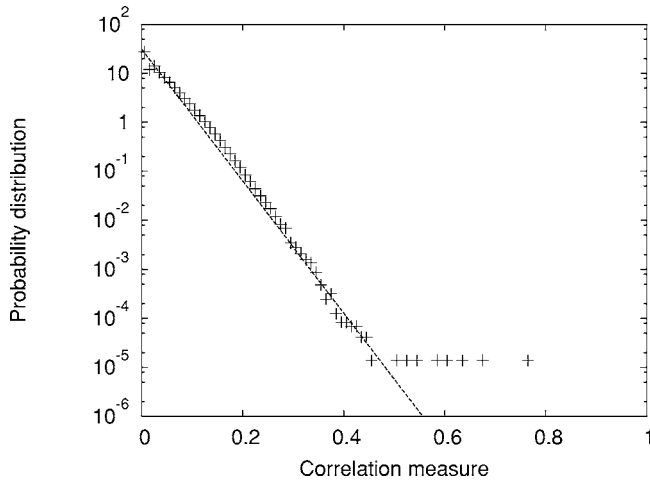


FIG. 2. Probability distribution of the matrix elements. The dashed line is the fitted exponential $\gamma e^{-\gamma C}$, with $\gamma=31$.

teners are linked in the unipartite representation. For instance, *Radiohead* fully connects 28% of the user community whatever the rest of their music library contents. This projection method definitely leads to an oversimplified and useless representation. We refine it by focusing on correlations between the users libraries. To do so, we define for each listener μ the n_G vector $\vec{\sigma}^\mu$:

$$\vec{\sigma}^\mu = (\dots, 1, \dots, 0, \dots, 1, \dots), \quad (1)$$

where $n_G=617\,900$ is the total number of groups in the system, $\mu \in [1, 35\,916]$ and where $\sigma_i^\mu=1$ if μ owns group i and $\sigma_i^\mu=0$ otherwise. This vector is used as the *individual musical signature* (IMS), as mentioned in the introduction.

In the following, we make a selection in the total number of users for computational reasons. To do so, we have analyzed a subset of $n_p=3806$ persons having a number of groups between $[115, 165]$, see Fig. 3, i.e., around the average value 140. In order to quantify the correlations between two persons μ and λ , we introduce the symmetric correlation measure

$$C^{\mu\lambda} = \frac{\vec{\sigma}^\mu \cdot \vec{\sigma}^\lambda}{\|\vec{\sigma}^\mu\| \|\vec{\sigma}^\lambda\|} \equiv \cos \theta_{\mu\lambda}, \quad (2)$$

where $\vec{\sigma}^\mu \cdot \vec{\sigma}^\lambda$ denotes the scalar product between the two n_G vectors, and $\|\cdot\|$ is its associated norm. This correlation measure, that corresponds to the cosine of the two vectors in the n_G -dimensional space, vanishes when the persons have no common music groups, and is equal to 1 when their music libraries are strictly identical.

At this level, the search for social communities requires therefore the analysis of the $n_p \times n_p$ correlation matrix $C^{\mu\lambda}$. A first relevant quantity is the distribution of the matrix elements $C^{\mu\lambda}$ that statistically characterizes the correlations between listeners. Empirical results show a rapid exponential decrease of the correlation distribution (Fig. 2), that we fit with $31e^{-31C}$, so that people in the sample are clearly discriminated by their music taste, i.e., they are characterized by nonparallel vectors. This justifies the use of his or her music library as a unique IMS of the listener.

III. PERCOLATION IDEA-BASED FILTERING

A. Listeners network

In order to extract communities from the correlation matrix $C^{\mu\lambda}$, we use the following method. We define the filter coefficient $\phi \in [0, 1[$, and filter the matrix elements so that $C_f^{\mu\lambda}=1$ if $C^{\mu\lambda} > \phi$, and let $C_f^{\mu\lambda}=0$ otherwise. In Fig. 3, we show the graph representation of the filtered matrix for increasing values of ϕ . For the sake of clarity, we have only depicted the individuals that are related to at least one person, i.e., *lonely* persons are self-excluded from the network structure, whence from any community. One observes that, starting from a fully connected network, increasing values of the filtering coefficient remove less correlated links and lead to the formation of communities. These communities first occur through the development of strongly connected components [25], that are peninsulas, i.e., portions of the network that are *almost* disconnected from the main cluster, themselves connected by intercommunity individuals. Further increasing the filtering coefficient value leads to a removal of these intercommunity individuals, and to the shaping of well-defined islands, completely disconnected from the main island. Let us stress that this systematic removal of links is directly related to percolation theory. It is therefore interesting to focus on the influence of the network structuring along percolation transition ideas. To do so, we compare the bifurcation diagram of the empirical data with that obtained for a randomized matrix, i.e., a matrix constructed by a random re-disposition of the elements $C^{\mu\lambda}$. As shown in Fig. 4(a), the correlated structure of the network broadens the interval of the transition as compared to the uncorrelated case. Moreover, the correlations also seem to displace the location of the bifurcation, by requiring more links in order to observe the percolation transition. This feature may originate from community structuring that restrains network exploration as compared to random structures [27].

As a first approximation, we restrict the scope to the formation of islands in the matrix analysis, i.e., to the simplest organized structures. From now on, we therefore associate the breaking of an island into subislands to the emergence of a new subcommunity, and, pursuing the analogy, we call the largest connected structure the *mainstream community*. Before going further, let us stress that the projection method described above is exactly equivalent to that of Ref. [15] when $\phi=0$.

In the following, we use a branching representation of the community structuring (see Fig. 5 for the sketch of three first steps of an arbitrary example). To do so, we start the procedure with the lowest value of ϕ , here $\phi=0.2$, and we represent each isolated island by a square whose surface is proportional to its number of listeners. Then, we increase slightly the value of ϕ , e.g., by 0.01, and we repeat the procedure. From one step to the next step, we draw a bond between emerging subislands and their parent island. The filter is increased until all bonds between nodes are eroded (that is, there is only one node left in each island). Applied to the above correlation matrix $C^{\mu\lambda}$ (Fig. 6), this representation leads to a compact description of the series of graphs as those found in Fig. 3. Moreover, the snake structure gives

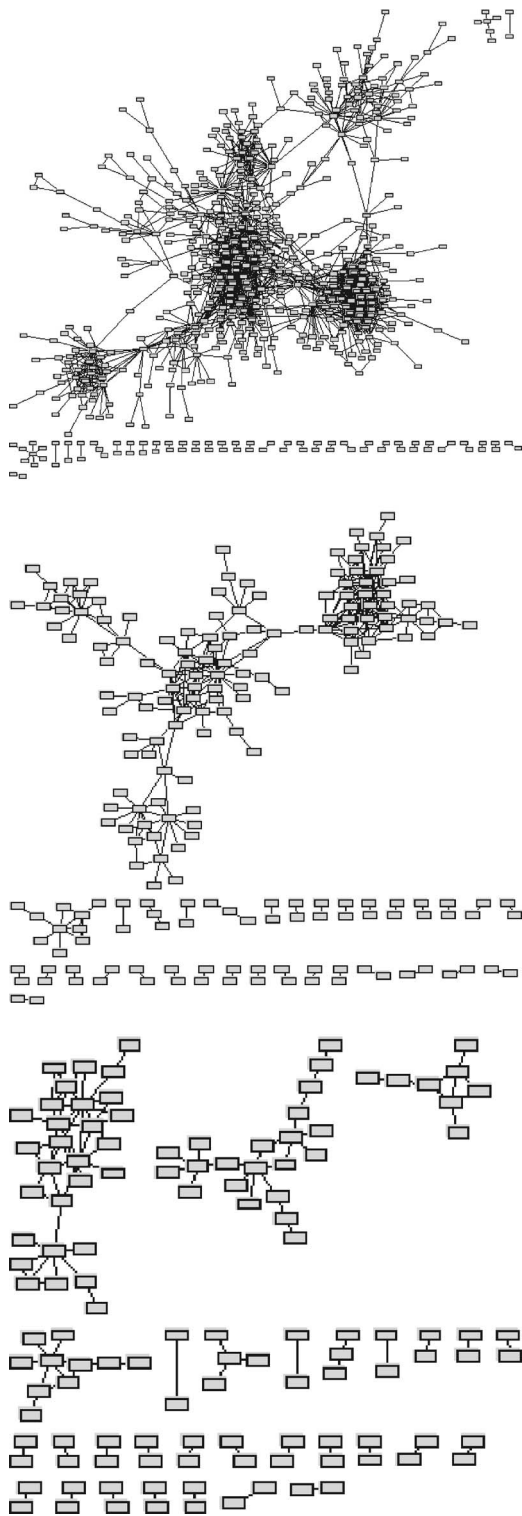


FIG. 3. Graph representation of the listener filtered correlation matrix for three values of the filter parameter $\phi=0.275$, $\phi=0.325$, and $\phi=0.35$, displayed from top to bottom. The graphs were plotted thanks to the VISONE graphical tools [26].

some insight into the diversification process by following branches from their source toward their extremity. The longer a given branch is followed, the more likely it is forming a well-defined community.

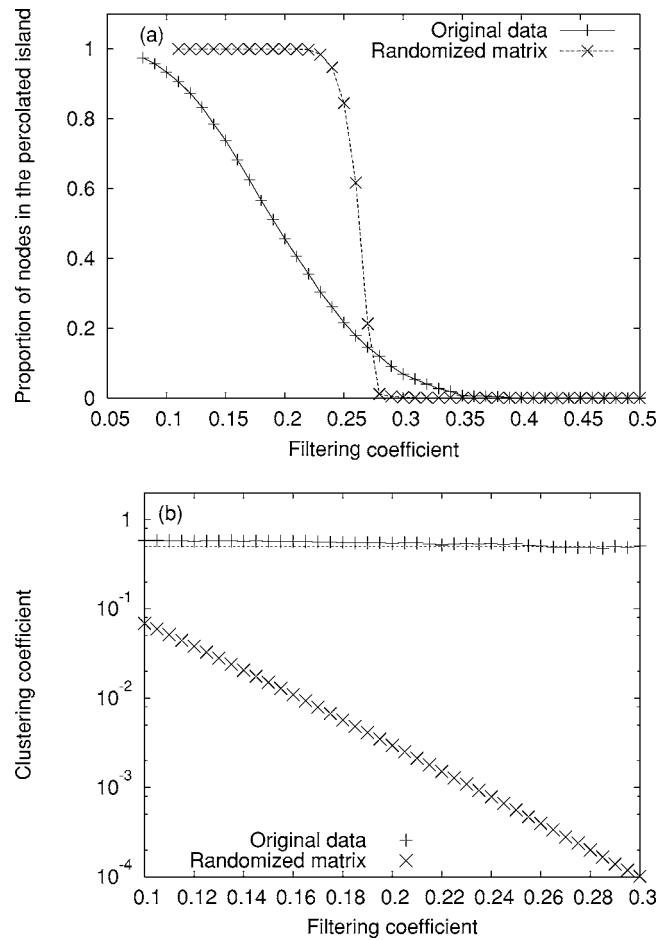


FIG. 4. (a) Proportion of nodes in the percolated island as a function of the filtering coefficient ϕ , for the original listeners correlation matrix $C^{\mu\lambda}$ and the corresponding randomized matrix; (b) Dependence of the clustering coefficient C on the filtering coefficient ϕ . The dashed line, at $C=0.5$, is a guide for the eye.

In order to focus on collective effects, we have studied in detail the behavior of the clustering coefficient [15], that is a measure of the density of triangles in a network, a triangle being formed every time two of one node's neighbors are related between them. This quantity is a common way to measure social effects in complex networks, and measures, roughly speaking, whether the friend of a friend is a friend. In Fig. 4(b), we plot the dependence of this quantity C vs the filtering coefficient ϕ . Moreover, in order to highlight the effects of correlations, we compare the results with those obtained for the above randomized matrix. Our analysis shows a very high value of C , almost ϕ independent for the original matrix. This suggests that the way people acquire their music taste is a highly social mechanism, likely related to its identification role as described in the introduction.

B. A typical individual music signature

Before focusing on the genre fixation of music groups, we give here, as an empirical example, the music library of one person. This list is intended to indicate the diversity of

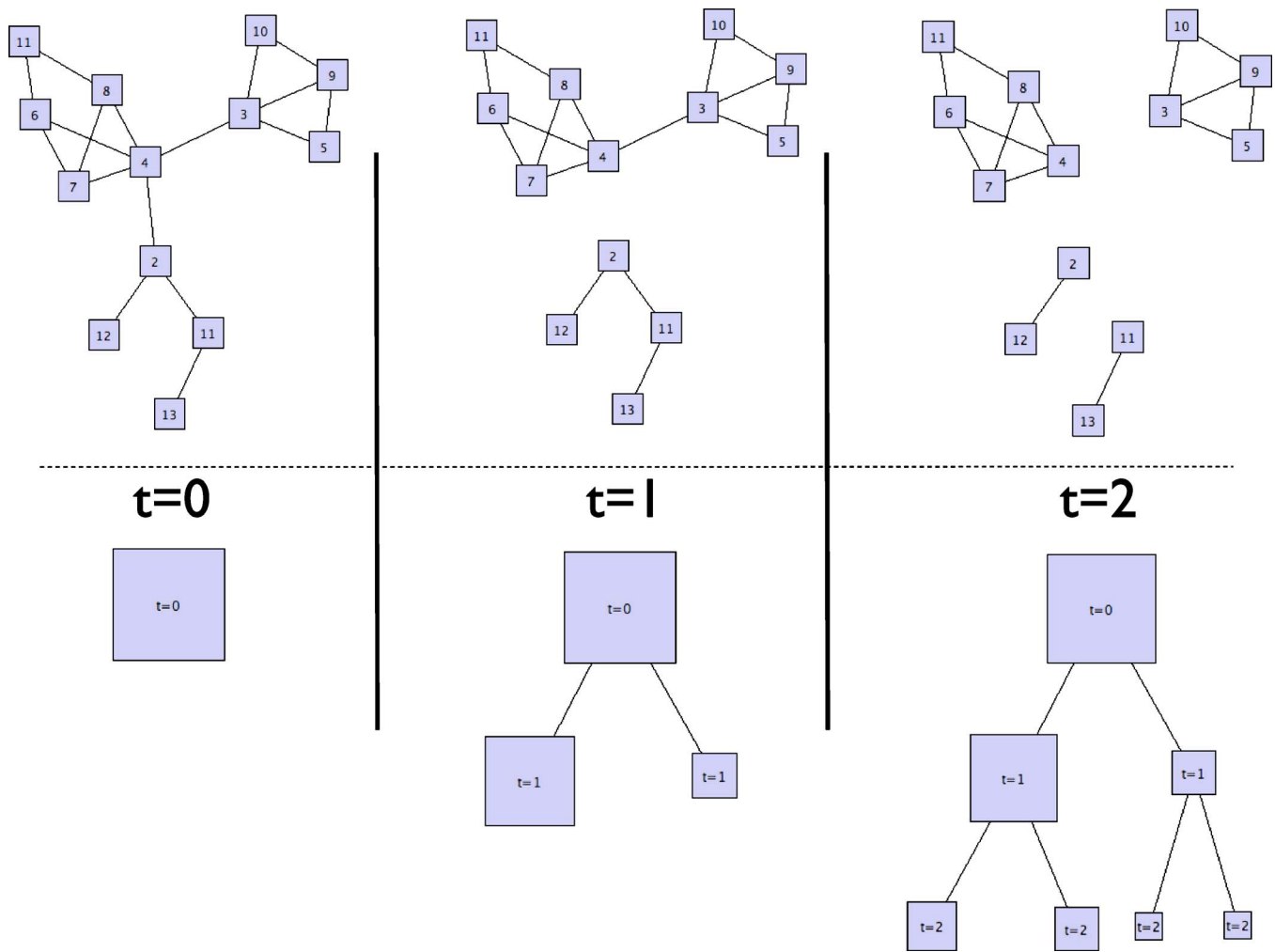


FIG. 5. (Color online) Branching representation of a correlation matrix. At each increasing step ($t=0, 1, 2$) of the filter ϕ , links are removed, so that the network decomposes into isolated islands. These islands are represented by squares, whose size depends on the number of nodes in the island. Starting from the largest island, branches indicate a parent relation between the islands. The increasing filter method is applied until all links are removed.

groups that characterize a listener, as well as his or her community. We write in bold the music groups that are common to his or her subcommunity, found by the PIB technique, and in normal characters those that are owned only by the individual. There are 117 different music groups.

Music library: *Air* + **New Order** + *Jane's Addiction* + *DJ Krush* + **Massive Attack** + **DJ Shadow** + **Beastie Boys** + *Orbital* + **Blur** + **Pixies** + *Leftfield* + **Sonic Youth** + **David Bowie** + *Primus* + **Jeff Buckley** + *The Smiths* + **Daft Punk** + **Joy Division** + **Smashing Pumpkins** + **Chemical Brothers** + *Korn* + **Eminem** + *Nirvana* + *Radiohead* + **Granddaddy** + *Travis* + **Oasis** + *PJ Harvey* + **Manic Street Preachers** + *Roots Manuva* + *Unkle* + **Linkin Park** + *Atari Teenage Riot* + **Kula Shaker** + *The Police* + *James Iha* + **Semisonic** + **Weezer** + *Anastacia* + **Rob Dougan** + **Eels** + *Fatboy Slim* + **Green Day** + *Lostprophets* + **System of a Down** + *U.N.K.L.E.* + *El-P* + **Bee Gees** + **Duran Duran** + **Therapy?** + *The Prodigy* + **Foo Fighters** + **JJ72** + *Alkaline Trio* + **The Beatles** + **Incubus** + *Prodigy* + **Muse** + *And You Will Know Us By The Trai* + **Jimmy Eat World** + **Ash** +

Rival Schools + *Cher* + *At The Drive-In* + *Johnny Cash* + *Mansun* + *Queens of the Stone Age* + **Basement Jaxx** + *Dave Matthews Band* + *Dj Tiesto* + *Cast* + **The Strokes** + *Anthrax* + *Ian Brown* + **Saves The Day** + *Morrissey* + *Police* + *Modest Mouse* + *Interpol* + *St Germain* + **The Beach Boys** + *Bonnie Tyler* + *Theme* + **Fenix*TX** + **Snow Patrol** + *The Cooper Temple Clause* + *Buddy Holly* + **Nada Surf** + *onlinedrawing* + *Michael Kamen* + *Remy Zero* + *Ernie Cline* + **Quicksand** + *Olivia Newton John* + **Polar** + *Ikara Colt* + *Keiichi Suzuki* + *Rivers Cuomo* + *Paddy Casey* + **Billy Talent** + *Mireille Mathieu* + *Jack Dee* + *Tomoyasu Hotei* + *Daniel O'Donnell* + *Hope Of The States* + **Franz Ferdinand** + *The Shadows* + **THE STILLS** + **The RZA** + *The Mamas and the Papas* + *Melissa Auf Der Maur* + *Barron Knights* + **The Killers** + **R.E.M.** + **Jay-Z** + **DJ Danger Mouse** + *Pras Michel Feat ODB and Maya* + *The Monks Of Roscrea*.

Obviously, this person belongs to a music community characterized by a mixture of the usual music genres, including Pop/Rock, 80's Pop, Electro, Alternative, etc. This eclec-

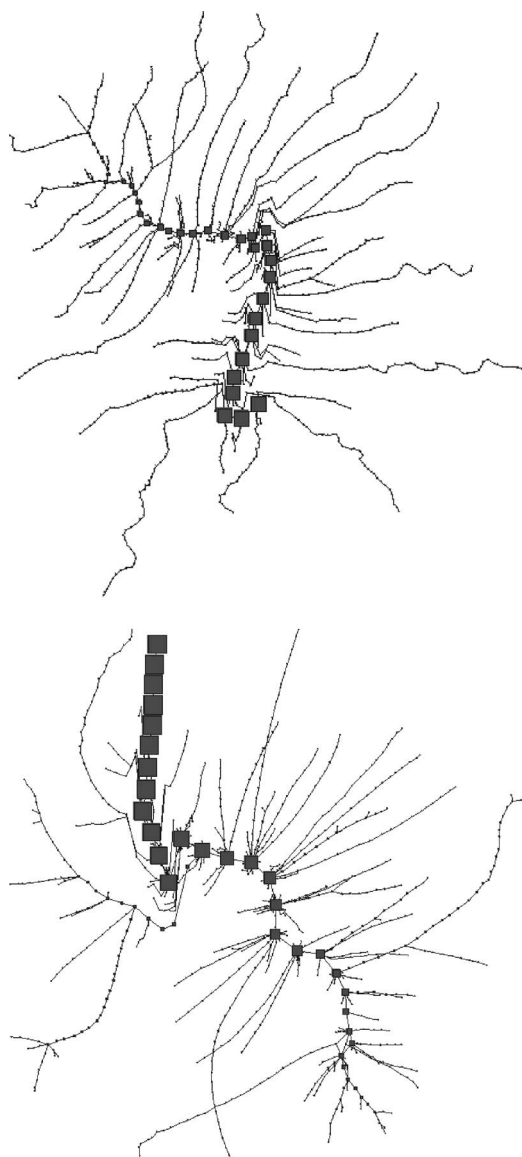


FIG. 6. In the upper figure, branching representation of the listener $C^{\mu\lambda}$ correlation matrix. The filtering, with parameter ranging from 0.2 to 0.5 (from bottom to top) induces a snake of squares at each filtering level. The shape of the snake as well as its direction are irrelevant. In the lower figure, branching representation of the music groups correlation matrix, the filtering parameter ranging from 0.3 to 0.6 (from top to bottom).

ticism indicates the inadequacy of such music subdivisions to characterize individual and collective listening habits.

C. Music groups network

In view of the above, it is interesting to introduce a new way to build music subdivisions, i.e., based upon the listening habits of their audience. To do so, we have applied the PIB approach to a sample composed of the top 5000 most-owned groups. This limited choice was motivated by the possibility to identify these groups at first sight. Each music group is characterized by its signature, that is, a vector,

$$\vec{\gamma} = (\dots, 1, \dots, 0, \dots, 1, \dots), \quad (3)$$

of n_L components, where $n_L=35\,916$ is the total number of users in the system, and where $\gamma_\mu^i=1$ if the listener μ owns group i and $\gamma_\mu^i=0$ otherwise. By doing so, we consider that the audience of a music group, i.e., the list of persons listening to it, identifies its signature, as we assume that the music library characterizes that of an individual.

The next step consists in projecting the bipartite network onto a unipartite network of music groups. To do so, we build the correlation matrix for the music groups as before, and filter it with increasing values of the filtering coefficient. As previously, the action of filtering erodes the nodes, thereby revealing a structured percolated island (Fig. 7) that breaks into small islands. The resulting tree representation of the correlation matrix (Fig. 6) shows clearly long persisting branches, thereby suggesting a high degree of common listenership. Poring over the branches of the top 5000 tree [28], we find many standard, homogeneous style groupings. Amongst these homogeneous cliques, there are [George Strait, Faith Hill, Garth Brooks, Clint Black, Kenny Chesney, Shania Twain, Alan Jackson, Martina McBride, Alabama, Tim McGraw, Reba McEntire, Diamond Rio, John Michael Montgomery, SheDaisy, Brooks and Dunn, Clay Walker, Rascal Flatts, Lonestar, Brad Paisley, Keith Urban], [Kylie Minogue, Dannii Minogue, Sophie Ellis Bextor], [Serge Gainsbourg, Noir Désir], [Billie Holiday, Glenn Miller, Benny Goodman], [Morrissey, Faith No More, Machine Head, The Smiths, Rammstein, Smashing Pumpkins, Slipknot, Tomahawk, Mr. Bungle], that are country, dance pop, geographically localized, i.e., France, swing jazz, and rock groupings, respectively.

In contrast, many of the islands are harder to explain from a standard genre-fication point of view. In some cases, the island may be homogeneous in one music style, but show some unexpected elements, like [Spain In My Heart (Various), The Pogues, Dave Brubeck Quartet, Crosby, Stills, Nash and Young, Phil Ochs, Billy Bragg, Clem Snide, Sarah Harmer, Mason Jennings, Kirsty MacColl, tullycraft, Ibrahim Ferrer, Sarah Slean, Penguin Cafe Orchestra, Pretenders, Joe Strummer and The Mescaleros, Freezepop] that is a folk-folk cluster, with odd members like the Brubeck Jazz Band, for example. But other groupings defy monolithic style categorization, like [The Jon Spencer Blues Explosion, Yello, Galaxie 500, Prince and the Revolution, Ultra Bra, Uriah Heep, Laurent Garnier], [Crosby, Stills, Nash and Young, Orb, Zero 7, Royksopp, Stan Getz]. The latter include unexpected mixtures of Indie Rock/Funk/Hard Rock/Dance, and Folk/Electro/Jazz, respectively.

Consequently, the PIB approach reveals evidence of unexpected collective listening habits, thereby uncovering trends in music. As a matter of fact, these anomalous entities have been shared by multiple listeners. This seems to confirm the role of collective listening habits in the individual building of music taste. It is important to note that the PIB method neglects the relevance of the main island structuring by identifying “music genres” and “listener communities” with isolated islands. It is obviously a drastic simplification that may lead to the neglect of pertinent structures, and there-

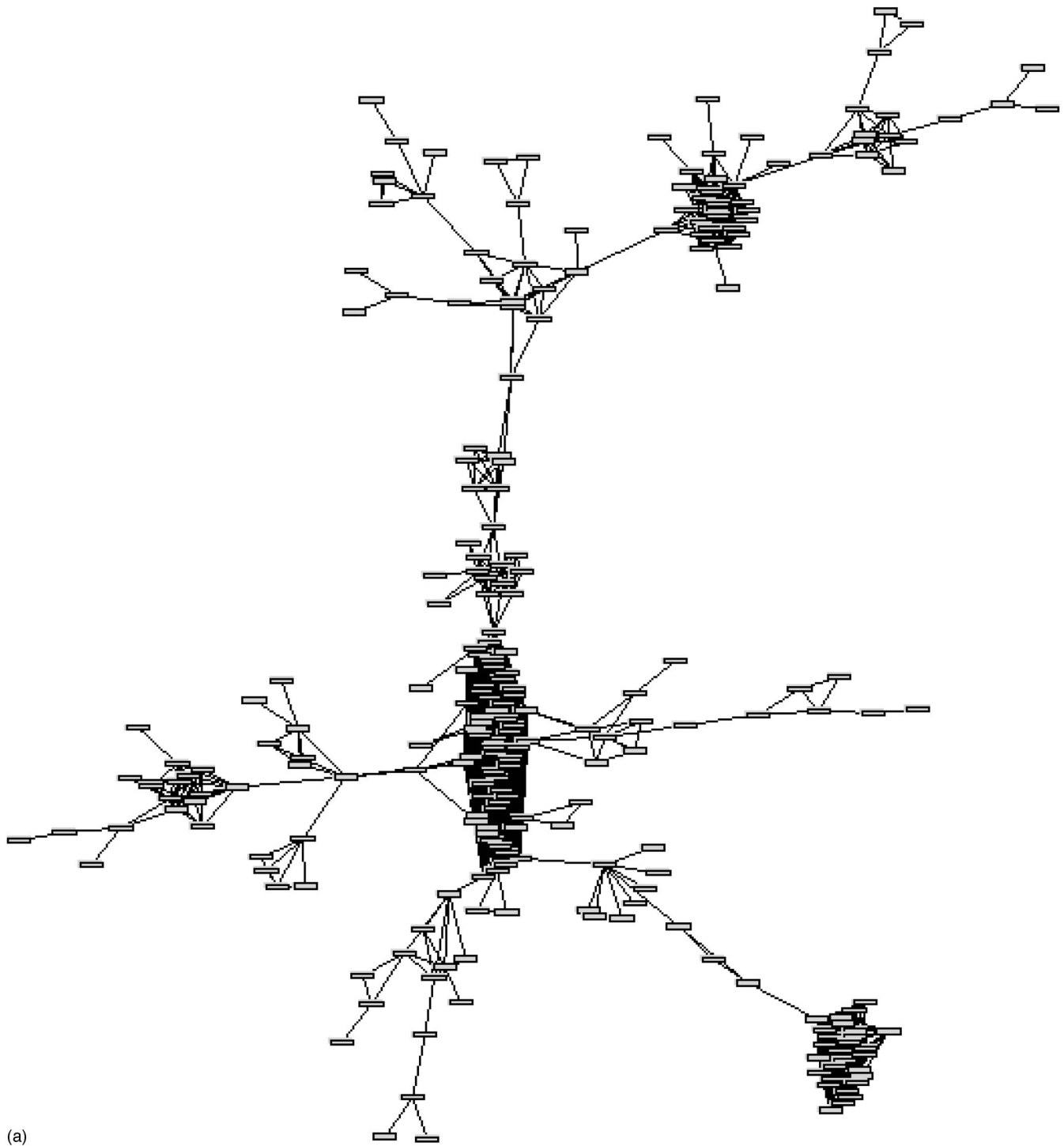


FIG. 7. In the upper figure, typical percolated island of music groups for $\phi=0.45$. It is composed of 247 nodes and 4406 links. In the lower figure, zoom on a small structure of the percolated island, that is obviously composed of *guitar heroes*, e.g., *B.B. King*, *S.R. Vaughan*, *A.D. Meola*, etc. Let us also note that *S.R. Vaughan* appears through two different ways that are linked by our analysis.

fore requests a more detailed exploration of the network structure.

IV. RANDOM WALK EXPLORATION

In this section, we consider an alternative method for revealing the internal structures of the network. The method is

based on a random walking exploration of the percolated island. The random walk (RW) starts at some node, i.e., the *initial node*. At each time step, we choose randomly one of its links, and move the walker to the connected node. Moreover, we keep track of the distance from the occupied node to the original node d_{0i} as a function of time i . By definition, the distance between two nodes is the length of the smallest

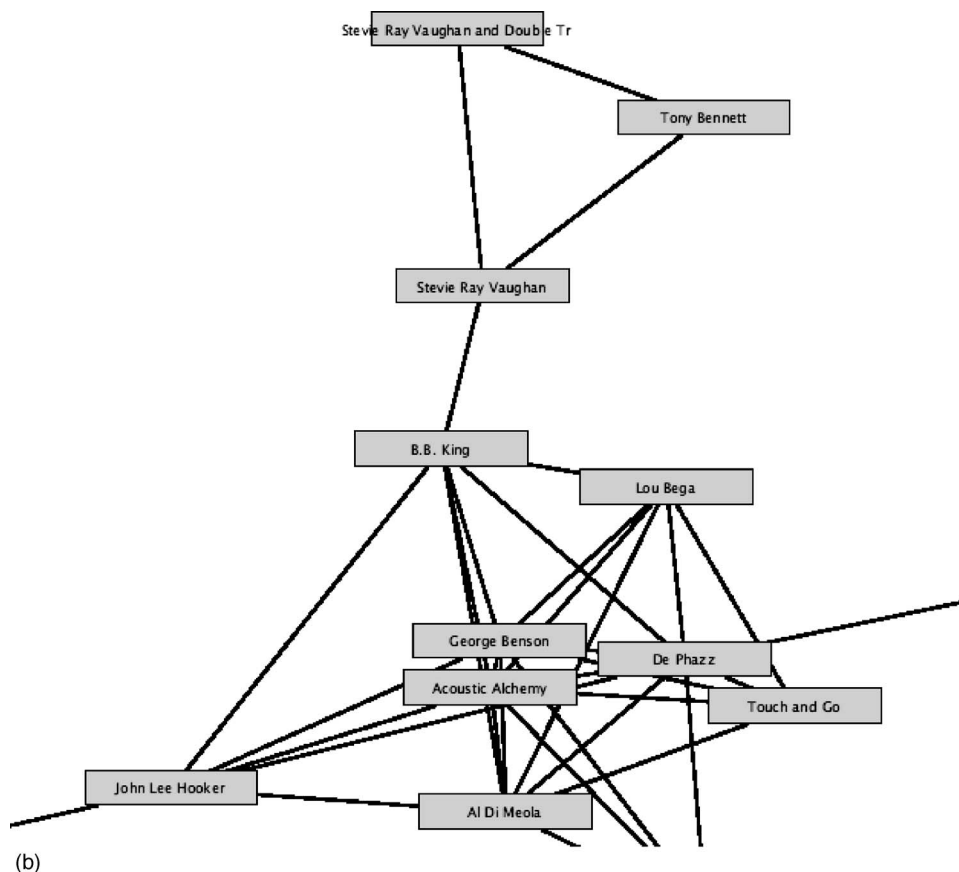


FIG. 7. (Continued).

path between them. The initial node is chosen to be the central node of the percolated island, namely the node c that minimizes the average distance with other nodes in the island:

$$\langle d \rangle = \frac{1}{(n_I - 1)} \sum_{i \neq c}^{n_I} d_{ci}, \tag{4}$$

where n_I is the number of nodes in the island.

In the following, we focus on the percolated island of Fig. 7, that is composed of $n_I=247$ nodes, and 4406 links. The percolated island clearly exhibits peninsulae, that link alike music groups. For instance, the cluster in the center of the figure is “hard rock” oriented, with music groups like *The killing tree*, *Unearth*, *Murder by Death*, etc. This is also illustrated in the lower graph of Fig. 7, where we zoom in on a small structure that encompasses *guitar heroes*, e.g., *B.B. King*, *S.R. Vaughan*, *A.D. Meola*, *G. Benson*, etc. In the case under study, the central node is the music group *Murder by Death*, that is located in the hard rock cluster.

The resulting time series [Fig. 8(a)], that is directly related to the subjacent path geometry, seems to indicate the existence of different time scales, associated with the large-scale structures in the network. In order to analyze the time series, we have focused on the probability of return toward the initial node. To do so, we have measured the time intervals τ between two passages of the walker on the initial node, and calculated the distribution $f(\tau)$ of these time inter-

vals. Moreover, in order to study the rare events associated to the tail of the distribution, we focus on the risk function $R(t) = \int_t^\infty f(\tau) d\tau$. By construction $R(0)=1$ and $R(\infty)=0$. The results, that are plotted in Fig. 8(b), clearly reveal two time scales: a rapid time scale (80 time steps) that determines the internal dynamics in one cluster; a slow time scale (2200 time steps) that characterizes the passage from one cluster to another one. Let us stress that detrended fluctuation analysis of the random walk [29] leads to the same conclusion.

V. PERSONAL IDENTIFICATION–COMMUNITY IMITATION MODEL

The empirical results of the previous section suggest that a person’s musical taste derives from an interplay between personal identification, i.e., his/her individual choice, and community imitation, i.e., the collective trend. In order to test this assumption, we introduce the PICI model where personal music libraries build through two processes. On one hand, collective effects, originating from social interactions between individuals, are mimicked by an exchange of music groups between *similar* individuals. In order to define this similitude between two persons, we compare their music libraries, and favor the pair interactions between people having alike music taste, as in a Potts model [30]. On the other hand, there are individual mechanisms that push people to distinguish themselves from their community. We model such a dynamics by individual random choices. We neglect

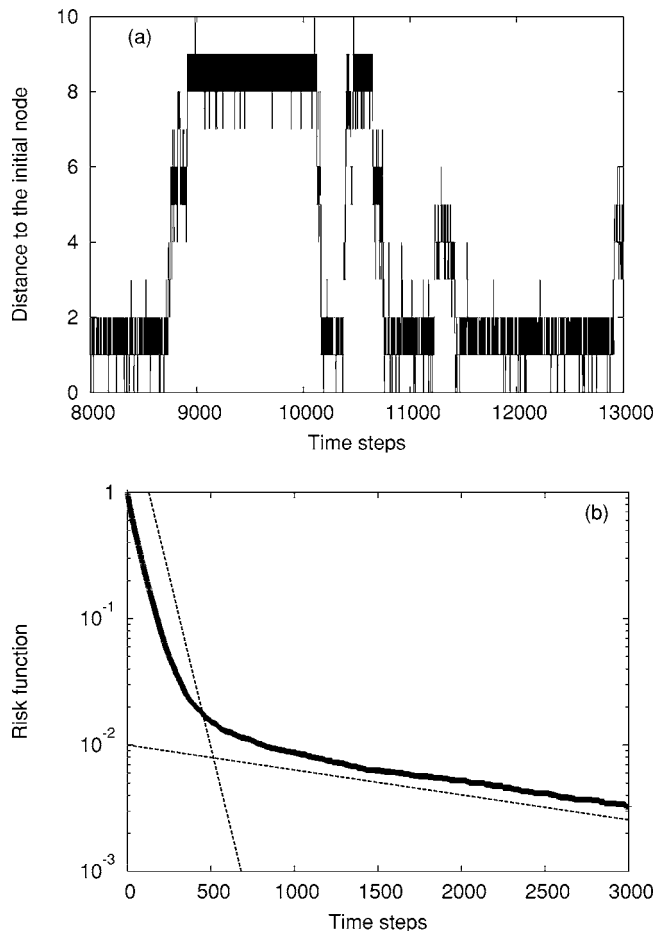


FIG. 8. (a) Time evolution of the distance to the initial node during the RW on the network of Fig. 7. The network exploration exhibits clearly the passage from one cluster to another, followed by long stopovers in the latter cluster. (b) Risk function $R(t)$ of the signal. The dashed lines are guides for the eye, and represent the exponential relaxations $e^{-t/80}$ and $e^{-t/2200}$.

the effect of an external field, like advertising, on an individual behavior. Moreover, in order to reproduce the observed degree distributions of the bipartite graph [22], we assume that the networks are growing in time. This is done in a way that music groups are chosen with preferential attachment [14], i.e., with a probability simply proportional to their audience.

These requirements are put into form as follows. The system is composed by $L(t)$ users and $M(t)$ music groups, that are initially randomly linked. At each (Monte Carlo) time step, three processes may occur:

(i) A new user may enter the system, with probability p_I . His or her library contains one music group, chosen randomly in the set of previous groups with preferential attachment.

(ii) A randomly picked user adds a new music group to the library, with probability p_N . This new group appends to the collection of available music in the system.

(iii) Two randomly chosen users exchange their music knowledge, with probability p_E .

The pair is selected with a probability proportional to $e^{(\cos \theta_{\mu\lambda} - 1)/T}$, where $\theta_{\mu\lambda}$ is the angle between the vectors of

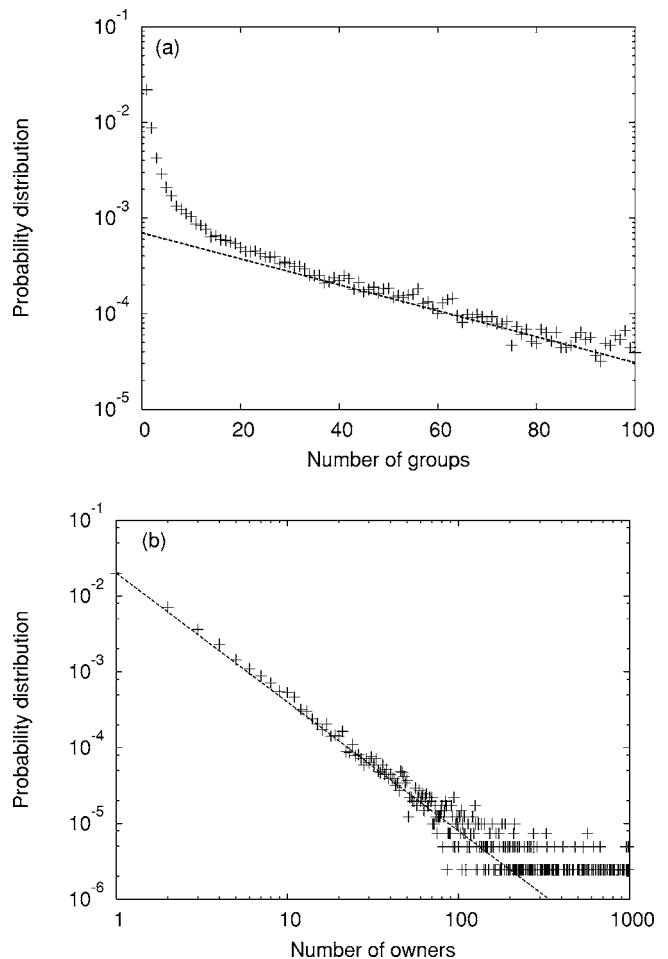


FIG. 9. Simulation results of PICIM for parameters given and explained in the text: (a) distribution of the number of music groups per user; (b) distribution of the audience per group. The dashed line is the power law $\sim n^{-1.7}$.

their music libraries [Eq. (1)], defined by their cosine [Eq. (2)]; the *temperature* T is a parameter that represents the ability of qualitatively different communities to mix together. If the pair is selected, we compare the two music libraries, and give to each user a fraction of the unknown groups of his or her partner. Let us stress that this rule ensures preferential attachment for the music groups.

Some representative results of the simulations obtained from the model are selectively shown in Fig. 9, for a typical simulation set, with $p_I=0.02$, $p_N=0.03$, $p_E=0.03$, and $T=0.13$. A complete analysis of the PICI model phase space variables and the dynamics will be presented elsewhere. The simulations were stopped after 200 time steps/node, in a system composed by 22 800 users, 15 126 music groups, and 442 666 links.

The degree distributions of the bipartite graph are depicted in Fig. 9. The results reproduce quite well the exponential and the power-law features experimentally found (Fig. 1). For the group distribution, the exponent is close to the empirical value 1.8. Moreover, different simulations show that this value remains in the vicinity of 2 for a large set of parameter values.

For the user distribution, simulations also reproduce the deviations from the exponential for small number of groups n_G , as observed in Fig. 1. We have noticed (unshown) that these deviations diminish for increasing values of T . This uncovers that the self-organizing mechanisms associated to community structuring are responsible for the extreme deviations.

The dependence of the clustering coefficient C on the filtering coefficient has also been considered. It is found that the the simulations reproduce qualitatively well the almost constant high value of C found in Fig. 4. However, this behavior ceases to be observed for large values of the temperature, i.e., in systems where collective effects do not develop by construction of the model. This seems to confirm the crucial competing roles played by individual choices and community influence in order to reproduce the observed data.

VI. CONCLUSION

In this paper, we study empirically the musical behaviors of a large sample of persons. Our analysis is based on complex network techniques, and leads to the uncovering of individual and collective trends from the data. To do so, we use two methods. On one hand, we use percolation idea-based techniques that consist in filtering correlation matrices, i.e., correlations between the listeners and music groups. Moreover, the communities and music genres are visualized by a branching representation. On the other hand, we explore the structure of the main percolated island by randomly walking the network. The goal is to map its internal structure and correlations onto a time series, that we analyze with standard statistical tools.

The method allows us to reveal nontrivial connections between the listeners and music groups. It is shown that if some empirical subdivisions respect the standard genre classification, many subdivisions are harder to explain from a standard genre-fication point of view. These collective listening habits, that do not fit the neat usual genres defined by the music industry, represent the *nonconventional* taste of listen-

ers. They could therefore be an alternative *objective* way to classify music groups. These collective genre-hopping habits also suggest a growing eclecticism of music listeners [28], that is driven by curiosity and self-identification, in opposition to the uniform trends promoted by commercial radios and *Major* record labels [31].

We would like to point that the above methods should help finding and visualizing structures in a large variety of networks, e.g., the detection and classification of trends in marketing, show business, and financial markets. Applications should also be considered in taxonomy [32], in scientometrics, i.e., how to classify scientific papers depending on their authors, journal, year, keywords, etc. and in linguistics [33]. From a more theoretical point of view, this work is closely related to the theory of hidden variables [34–36], i.e., the hidden variables being here some intrinsic property of the music groups [37], and should provide an empirical test for this theory.

We introduce a simple grow model, that reproduces quite well the results obtained from the empirical data, i.e., the observed degree distributions of the networks. It is important to point out that the ingredients of the model are very general, i.e., imply competition between personal identification and community imitation (PICI). Consequently, PICI should apply to a larger variety of systems than the music networks hereby investigated, but also to other networks such as collaboration networks in science [22]. In a statistical physics sense, the model contains Potts model-like ingredients for opinion and taste formation.

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