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Using Relational Class Analysis:
The Case of the Cultural Omnivore Reexamined

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Abstract

Sociologists often describe culture as a repertoire of shared understandings. But because the meanings that social actors attribute to symbols and actions emerge from the multiple associations they make between them, delineating collectively shared understandings is not a straightforward task. Standard quantitative sociological practice, which relies on the assumptions of what Abbott (1988) calls 'general linear reality', falls short of addressing such complexity in two significant ways: first, it overlooks the multivocality of cultural objects by presupposing that the effects that social attributes have on cultural interpretations are consistent across individuals, and second, it fails to acknowledge that people may have different behaviors or opinions on particular issues, but still agree on the structures of relevance and opposition that make symbols and actions meaningful. In this paper, I introduce a new method—Relational Class Analysis—that simultaneously compares differences between individuals, and within their sets of attitudes, as a means to detect groups with underlying shared understandings of a particular social domain. To demonstrate the utility of this method, I use it to revisit the cultural omnivore thesis by reexamining Americans' attitudes toward musical genres. I find further support for the claim that high-status individuals have replaced cultural snobbism with inclusiveness, but also demonstrate the existence of two competing and systematically overlooked logics of distinction: one that continues to distinguish between high- and low-brow music, the other which distinguishes between traditional and contemporary musical preferences. These findings complicate, and in some ways challenge, contemporary understandings of cultural omnivorousness.

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Introduction

What do sociologists mean when they describe culture as a repertoire of shared understandings? Whereas early cultural sociologists drew on the notion of culture as fixed sets of internalized values and rules that consistently prescribe behavioral responses, contemporary theories maintain that social meaning is embedded in complex relational networks (Emirbayer 1997; Mohr 1998; Mohr and White 2008), infusing cultural objects with multivocality that can elicit a variety of shared understandings (Griswold 1987; Schudson 1989; Eliasoph and Lichterman 2003; Swidler 1986). If culture indeed inheres in the symbolic building blocks that are replicated, albeit unsystematically, across individuals, then a major challenge for sociology is to operationally define what these shared understandings are, and how they can be measured. Such a task becomes particularly tricky when taking into account that people make sense of their everyday experiences as a function of their accumulated and idiosyncratic experiential knowledge of the world. It calls for a theoretical framework that is on the one hand amenable to empirical investigation, but at the same time refrains from simplistically reducing 'shared understandings' to sets of independent attitudes and behaviors.

But mainstream quantitative sociological practice, which relies predominantly on methods that assume a linear relationship between a set of independent predictors and an outcome, is ultimately ill-equipped to detect or account for such complexity (Abbott 1988). These conventional methods fall short of meeting the challenge of addressing cultural polysemy in two significant ways. First, they normally implicitly presuppose and consequently look for homogeneity in the relationship between explanatory variables and

their predicted outcome. But not all people organize their thinking about the world in similar ways; their beliefs and behaviors cannot be reduced to one, singular regression line. As Jepperson and Swidler (1994) remind us, Durkheim long ago insisted that 'shared' does not necessarily imply 'universal'. Moreover, 'shared' does not necessarily imply 'identical' either. People may have different behaviors or opinions on particular issues, but still agree on their relative significance, or the dimensions along which this significance is scaled (Martin 2000a). You and I may vehemently disagree on abortion, for example, yet still understand the debate to be hinged on women's right to command their bodies; others might see it predominantly as a matter of social welfare (Ferree 2003). The multivocality of social meaning therefore calls for a methodological approach that differentiates between groups who share an understanding of the structures of mutual relevance and opposition that define a particular domain, even if they take different positions on the elements that these structures comprise.

To address this challenge, I introduce the concept of *relationality*, which forms the basis for a method for identifying groups of relationally similar individuals in multivariate data—which I refer to as *Relational Class Analysis* (RCA)—as a means to complement conventional analyses that rely on central tendencies in aggregate data. Relationality is defined as the extent to which two individuals exhibit a similar pattern of association between measures of opinion on issues that constitute a particular social domain; it is interpreted as a measure of their shared understanding of the structure of that domain. A variety of methods for dealing with heterogeneity in multivariate data are available. But these either cluster respondents by comparing their responses independently, and consequently overlook relationships between variables, or look at the

associations between all respondents' attitudes in the aggregate, without taking into account that different respondents might have different patterns of association. RCA, on the other hand, induces shared understandings as emergent collective properties by simultaneously examining relationships *between* respondents and *within* their sets of attitudes.

Like other partitioning methods, RCA seeks to parse out groups, or classes, of likeminded individuals. Unlike these methods, however, it uses relationality to compare these individuals not on their attitudes *per se* but on the *patterns of relations between their attitudes*. It can be applicable to a variety of theoretical challenges that require solving the problem of population heterogeneity by detecting groups that vary with respect to patterns of relationship between variables. These may include the demarcation of groups whose ideas are structured by distinct institutional or cultural logics (Friedland and Alford 1991; Enfield 2000), the identification of cognitive schemata as supra-individual structures of representation (DiMaggio 1997), the operationalization of collective identity (Ashmore, Deaux and McLaughlin-Volpe 2004) or the detection of different strategies of action employed by groups of actors (Swidler 1986; Bourdieu 1990).

To demonstrate the applicability and utility of RCA, as well as to flesh out the theoretical assumptions on which it is based I use it to reexamine a classic problem in the sociology of culture: the much-debated rise of the "cultural omnivore". Since Peterson's (1992) introduction of the cultural omnivore thesis more than fifteen years ago, many studies have demonstrated the emergence of a new, inclusive logic of cultural distinction that has ostensibly supplanted, at least in Western societies, elitist preferences that follow

a more old-fashioned rationale of high- versus low-brow taste. More recent studies have qualified Peterson's thesis, arguing for greater heterogeneity in the manner by which omnivorousness is practiced. They all seem to accept, however, the assumption that cultural distinction is today largely organized along an axis of cultural inclusiveness. Using RCA to analyze Americans' musical preferences as tapped by the 1993 General Social Survey, I provide further support for Peterson's theory, but also demonstrate the coexistence of two other, competing and systematically overlooked logics of distinction: one that continues to distinguish between high- and low-brow music, the other which distinguishes between traditional and contemporary musical preferences. These findings complicate, and in some ways challenge, contemporary understandings of cultural omnivorousness.

The remaining text is divided into four sections. The first provides an overview of the theoretical motivation for using relationality and RCA as a means to operationalize the notion of shared understanding. The second goes into detail in describing how relationality is computed, and how RCA uses it to identify groups of individuals who share overlapping patterns of association in regard to a given social domain. In the third section, the value of RCA is demonstrated through the method's application to Americans' musical tastes. Finally, the fourth section concludes by discussing the methodological advantages and limitations of RCA, by offering further paths for enhancing it and by suggesting the ways in which it can be useful in shedding light on the supra-individual mechanisms through which culture operates and evolves.

Theoretical Foundations of Relational Class Analysis

The notion of shared representations is a central to contemporary theories of culture (Berger and Luckmann 1966; Eliasoph and Lichterman 2003). It suggests that culture does not exist as an abstract entity entirely external to individuals, but that it is simultaneously individuated and socially distributed. Shared representations are embodied in the signs that make up the symbolic and physical environments in which social actors operate—such as those produced by language, media, architecture and art—as well as in the mental structures these actors use as cognitive processing mechanisms to organize their knowledge about the world. If 'belonging' to a particular 'culture' or 'thought community' (Zerubavel 1997) implies that its members mediate their experiences using similar cognitive building blocks, then they presumably also employ similar reasoning in understanding and responding to the realities they encounter. But because these mental structures are not disseminated and enforced by a singular authoritative source—rather they emerge and are constantly renegotiated through communicative interaction between individuals, and the social institutions they produce—they are never implemented in identical forms across individuals. This makes defining and locating shared understandings a challenging task.

For example, consider the common portrayal of the American public as entrenched in a polarizing 'culture war'. Contra to popular assertions, studies that probe Americans' beliefs find that, by and large, they do not neatly fall on either side of the cultural fault lines that supposedly divide American society, and that their sociodemographic attributes are, at best, weak predictors of their attitudes on a variety of social issues (Fiorina, Abrams and Pope 2005; DiMaggio, Evans and Bryson 1996; Baldassarri and Gelman

2008). Assuming that merely by virtue of being American they all frame these issues in similar ways, or that if disaggregated sociodemographically the structural causes for their different understandings can be fully accounted for, obscures the complex ideational heterogeneity that underlies American political culture. Thus in order to delineate the shared understandings that inter-subjectively sort individuals into 'thought communities', it is necessary to define clearly, first, what is implied by the assertion that two or more individuals have a 'shared' understanding, and second, how shared understandings bring individuals together to form different ideational groups.

What are Shared Understandings?

To understand a social situation entails attributing meaning to it. But while the act of understanding intuitively implies a reflective process of deliberation, such meditation is, in actuality, quite rare. Rather, our ongoing experiences of reality are automatically processed by subconscious (or 'reflexive') cognitive systems (Lieberman, Gaunt, Gilbert and Trope 2002; Galdi, Arcuri and Gawronski 2008). They accomplish this task by relying on complex structures of mental representation—commonly referred to as schemas—that are built up incrementally through interaction with the environment (D'Andrade 1995; Fiske and Linville 1980). Schemas embody our taken-for-granted assumptions about the world. They are mechanisms that allow us efficiently and seamlessly to process sensory input by relying on prior knowledge. That our experiences of the world are understood in terms of the schemas they activate explains why categorization is constitutive of the process of understanding. We classify new information in terms of our previous understandings, reinforcing and habituating our biases. Some have suggested that because schematic representations mediate between the

institutionalized environment and individuals' routinized behaviors, they should be a central unit of analysis for the study of culture (Brubaker, Loveman and Stamatov 2004; DiMaggio 1997).

Yet thinking of culture in schematic terms poses a methodological challenge: schemas are not clear sets of behavioral rules but rather implicit recognition procedures that emerge from intricate associational links among salient aspects of our cognitively represented experiences (D'Andrade 1995). Unlike formal logic of the kind implemented in digital computers, they function as parallel, not sequential, processors (Lieberman et al 2002). This suggests that the meanings individuals attribute to their experiences should be thought of in relational terms (Mohr 1998; Emirbayer 1997); namely that when assessing people's understandings we should not consider the positions they have on particular issues independently, but the relationships between their positions on a variety of issues that make up a certain social domain. Conventional statistical methods are normally not designed to take such relationships into account.

Consider four hypothetical respondents to the 1993 GSS who were asked to rate their preferences for a variety of musical genres. The first, who is moderately positive toward most genres, strongly likes classical music and opera, and is indifferent toward country music and bluegrass. A second respondent, who is moderately hostile towards most musical genres in general, slightly likes classical music and opera, and vehemently dislikes country and bluegrass. Though these two respondents take different positions on all musical genres, the pattern of relationships between their musical preferences is identical: they both prefer highbrow music, and undervalue Americana. They seem to be employing the same logic in regard to the ordering of their musical preferences. A third

respondent, on the other hand, who is indifferent to most musical genres, strongly prefers country music and bluegrass, and vehemently dislikes both classical music and opera. This respondent exhibits a pattern of relationships between her musical preferences which is antithetical to those of the first and second respondents: unlike the first two, she prefers Americana and dislikes highbrow. But while she takes contradictory positions to the two other respondents, she is still exhibiting a similar understanding of the dimensions along which taste is structured.

People may frame their understandings of a given domain in similar terms, even if they take different substantive positions (Gamson and Modigliani 1989; Ferree 2003). Thus, despite their bitter ideological disagreements, even Ann Coulter and Michael Moore, two of the most vocal contemporary political commentators, seem to agree on the dimensions along which American political discourse is defined; yet others, often those less powerful or publicly visible, do not seem to perceive the debate through a clearly structured ideological polarity between liberalism and conservatism (Baldassarri and Gelman 2008). To have a shared understanding therefore does not imply having identical attitudes or behaviors; rather it suggests being in agreement on the structures of relevance and opposition that make actions and symbols meaningful.

Comparing how two individuals organize meaning therefore requires examining the associations between their attitudes. This calls for a method that looks at the extent of dissimilarity between the pairwise differences between their individual opinions. Consider a fourth hypothetical respondent to the 1993 GSS, who likes bluegrass, opera and classical music, but dislikes country. Unlike the other three, who seem to be following a logic that is structured on the traditional distinction between high- and low-

brow music, this respondent orders his musical preferences in relation to their popularity. Looking at the dissimilarity in the pairwise differences between respondents' evaluations allows us to tell these two ideational structures apart by distinguishing between (1) individuals who follow a similar relational pattern, even if disagreeing on particular issues; (2) those who follow opposite relational patterns, but still agree on the dimensions along which meaning is defined; and (3) those whose relational patterns are orthogonal, suggesting that they perceive the issues through different prisms altogether. I refer to the first two as relationally overlapping, and to the latter as relationally different. Conventional methods that compare observations by treating variables independently would have found our four respondents to be far apart from one another, overlooking the underlying relational similarities that the first three respondents share, despite the differences in their evaluations of particular types of music[1].

Comparing associations between people's attitudes allows measuring the extent to which they organize meaning in similar ways. But how do we progress from the dyadic level to delineating different 'thought communities' in the population as a whole? We can think of the individuals that make up this population as points on an imagined multidimensional 'belief space' (Martin 2000a). The social significance of a position in this space is not predetermined, but rather defined by the social profiles of those who occupy it. Culture, in this context, can be understood as the unspoken set of rules that tie beliefs together by restricting movement in this space along certain axes, which demarcate different social worlds (Martin 2002). Tracing the shared understandings that define different groups therefore requires uncovering these axes. Yet examining relationships between beliefs in the aggregate necessarily overlooks heterogeneity in

[1] See Appendix C for a comparison with other methods

people's belief patterns. The challenge therefore becomes identifying different groups that are characterized by uniquely consistent and internally coherent patterns of associations between attitudes. Rather than relying on the *a priori* assumption that these groups are defined by a particular social dimension, such an approach identifies emergent structures of meaning that inhere in the network of ideational similarities between individuals (Mohr and White 2008).

What is Relational Class Analysis?

Thinking of culture in relational terms in is not a novel idea. It was introduced by European structuralists almost half a century ago, and has influenced cultural theory ever since (Mohr 1998). But relational approaches often either look at the relationships between variables, for example when they induce meaning by considering the associations between concepts, categories, and symbols (Mohr 1994; Martin 2000b), or at the relationships between individuals, and how those give rise to and sustain meaning (Padgett and Ansell 1993; Mark 2003; Gould 2002). Accordingly, existing methods are designed to detect latent structures either by exclusively examining associations between variables (eg. multi-dimensional scaling, factor analysis), or by sorting respondents into groups by analyzing their relationships (eg. cluster analysis).But to account for shared understandings requires that we *simultaneously* examine the relationships between variables and individuals. Schema theory suggests that because meaning emerges from the associations between salient cognitive components, uncovering it requires tracing the multiple links between the variables used to measure them. Ideational heterogeneity, on the other hand, and the assumption that it inheres in emergent collective meaning structures that link groups of individuals, requires paying attention to ideational

similarities between actors. Outlining different sets of shared understandings therefore calls for a dual-relational method that is sensitive to relational patterns both *within* and *between* observations. Relational Class Analysis (RCA) is designed to address this challenge. It does so by relying on two operational concepts: relationality and networks.

Recall our hypothetical respondents from the previous section. To illustrate the concept of relationality, which stands at the core of RCA, their responses are visualized in Figure 1. Intuitively, relationality measures whether the components of two vectors of the same set of variables follow a similar pattern. In our example, this refers to the level of similarity in the ways two individuals organize their musical tastes. The patterns in respondents A's and B's musical tastes are identical, which translates to maximal relationality. Respondent C's pattern, on the other hand, is almost a mirror image of A's and B's, which suggests that the relationality between C and the two other respondents is negative. An additional respondent, labeled D in the figure, also displays a pattern that is different from A's and B's, as well as from C's. Yet unlike C, respondent D is not oppositional to the rest; his pattern of musical tastes is different but not antithetical to the other respondents. In schematic terms, respondents A, B and C exhibit the same logic of musical taste construction (even if C's opinions are opposed to those of A and B), as they all exhibit the same structure of relevance and opposition. Respondent D, on the other hand, exhibits a different logic altogether. RCA's task is to compute relationality between all pairs of observations and partition the sample into subgroups of relationally overlapping respondents such that those who subscribe to the same logic are clustered together. It accomplishes that by performing the following sequence:

1. Computing a measure of relationality for each pair of observations in the dataset, resulting in an n-by-n matrix. This matrix is referred to as the relationality matrix.
2. The relationality matrix is transformed into a sparse relationality network by setting statistically insignificant relationality values to zero.
3. RCA partitions the relationality network into subgroups of relationally similar observations using a network community detection algorithm.

In the remainder of this section, I discuss each of these phases in detail.

Computing Relationality

RCA depends on measuring pattern similarities between individuals' responses. The similarity between two observations is often expressed as Euclidean distance, which, in mathematical terms, measures the geometric distance between two vectors. Euclidean distance compares the coordinates comprising the two vectors independently, without taking into account the differences between the coordinates. Because it uses summed squares, it is also insensitive to the directionality of differences between the vectors. But if by having a shared understanding we mean that two individuals employ similar structures of relevance and opposition in constructing meaning, then the differences between the pairs of variables that represent these structures, and their directions, are important.

Relationality between two observation vectors is therefore defined as the extent to which the differences between all the pairs of values in each vector are identical. It is computed by iterating through all possible pairs of variables, and measuring their *relational similarity***,** which is defined as the arithmetic complement (on a zero to one standardized scale) of the absolute difference in the relative distances between these two

variables in each of the two vectors. The relational similarity is then signed, depending on whether or not the two distances are in the same direction. In other words, relationality measures the mean difference in magnitude and direction in the pairwise distances between variables in both vectors. The smaller the mean difference between distances, the greater the relational similarity between the vectors.

Formally, relationality between observations *i* and *j* in dataset X of N observations and K variables is defined as follows[2]:

$$(1) \qquad R_{ij} = \frac{2}{K(K-1)} \sum_{k=1}^{K-1} \sum_{l=k+1}^{K} \left(\lambda_{ij}^{kl} \cdot \delta_{ij}^{kl} \right)$$

where:

$$(2) \qquad \delta_{ij}^{kl} = 1 - \left\| \Delta X_i^{kl} \right| - \left| \Delta X_j^{kl} \right\|$$

is the relational similarity for the variable pair {k,l} between observations i and j,

$$(3) \qquad \Delta X_i^{kl} = X_i^k - X_i^l$$

is the distance between the values of variables k and l for observation i, and

$$(4) \qquad \lambda_{ij}^{kl} = \begin{cases} 1 & \Delta X_i^{kl} \cdot \Delta X_j^{kl} \geq 0 \\ -1 & \Delta X_i^{kl} \cdot \Delta X_j^{kl} < 0 \end{cases}$$

is a binary coefficient that changes the sign of the relational similarity if both distances are in opposite directions.

[2] Each variable in dataset X is standardized over a zero to one range in order to make the variables comparable.

Like Pearson's correlation coefficient, relationality is bounded by -1 and 1[3]. This makes it easily interpretable. A relationality measure of 1 indicates that both observations are relationally identical, whereas a measure of -1 indicates maximal relational opposition between them (i.e. that all pairs of variables in each observation are exactly of opposite distance). Values in between these bounds reflect the expected signed relational similarity between a random pair of variables across the two observations. For example, if we were to compare the relational similarity between the same random pair of variables in observations B and D in Figure 1, we would expect it to be only 0.19. In other words, on a zero to one scale, the pairwise differences between both observations are only 0.19 identical in magnitude and direction.

Conceptually, relationality is an extension of Gini's inequality coefficient, but instead of measuring the mean relative difference between incomes, it measures the mean relative difference in the differences between all pairs of variables across two observations. Like Gini's coefficient, relationality is particularly suitable for measuring relational equality between observations because it avoids exclusive use of the mean for computing deviations, it refrains from using summed squares, and it is based on the differences between every pair of components (for a detailed discussion, see Coulter 1989: 52). Table 1 demonstrates how it differs from Euclidean distance. The two columns in the table list the standardized Euclidean distance and relationality measures for all pairs of respondents described in Figure 1. It clearly demonstrates that while Euclidean distance fails to differentiate meaningfully between these observations in terms of how they organize the field of musical genres, relationality succeeds.

[3] While the upper bound is always 1, the lower bound depends on data limitations, and in any case does not exceed -1. See appendix A for details.

Detecting Relationally Similar Groups

Because of its dyadic nature, relationality is particularly amenable to a network analysis approach. It produces a square matrix that contains relationality measures for all pairs of observations. This matrix can be thought of as a non-directional weighted network, in which each node corresponds to one observation, and each edge weight is the magnitude of relational similarity between the two observations it connects. Reorganizing the dataset as a network is an effective way of taking into account the multitude of relations between observations. As in conventional network analysis, the network produced by RCA represents ties between the individuals that comprise it. However unlike in most sociological network studies, the ties between individuals relate to their attitudinal similarities, not their interactive relationships. The assumption of heterogeneity implies that the task of identifying ideational groups requires dividing the network into communities of relationally associated individuals. Looking for subgroups of relationally similar respondents can therefore be approached as a network partitioning problem.

Before partitioning the network, it is worthwhile thinking about the values and significance of the relationality measures between pairs of respondents. Relationality between observations very rarely equals zero[4]. As a result, the network produced by RCA is extremely dense. But not all non-zero relationality values are informative. Relationality measures on either extreme of the 1 to -1 bound are of particular significance, as they

[4] In fact in the data used in the analysis below, only 0.02% of pairs had a relationality score equaling zero. This was consistent across simulations using randomly generated data. A zero relationality score occurs in the unlikely case in which the differences between all pairs of distances between variables across the two observations offset one another.

indicate that the two respondents employ similar principles in organizing the meaning domain, either in the same or opposite direction. On the other hand, measures in between these extremes indicate that the pair of respondents employ different (or orthogonal) but not oppositional rationales. RCA therefore removes ties that have relationality values that are statistically insignificant[5].

The network edges remaining after removing non-significant ties are those closest to either extreme of the -1 to 1 bound. Negative relationality between observations, suggests that the two respondents, like A and C in Figure 1, organize meaning in oppositional directions, but that they nevertheless agree on the dimensions along which meaning is defined. Consequently, RCA transforms all remaining network edge weights by their absolute value, treating both positive and negative weights identically. To demonstrate why absolute relationality values allow for the division of the sample into meaningful subgroups, consider a random subgroup of individuals who were asked five attitudinal questions. Figure 2 plots the average correlation strength between these five variables as a function of the average absolute relationality between all pairs of respondents in the sample[6]. The solid line corresponds to the fitted model, demonstrating that as the absolute relationality increases, so does the correlation, whether positive or negative, between the variables. In other words, as a group becomes more cohesive in terms of the relational overlap between its members, so do the patterns of association between its members' attitudes become more consistent. Partitioning the network into relationally overlapping subgroups therefore produces a natural division of the population into communities with distinct covariance structures between attitudes.

[5] See Appendix A for details on the bootstrapping method used to establish significance.
[6] These results are based on a series of simulations with randomly generated data.

Hierarchical clustering and blockmodeling algorithms are commonly used in social network analysis for detecting community structure (Wasserman and Faust 1994). More recently, attention to the network community problem from the physics and mathematics communities has led to the development of several new network partitioning algorithms (for a review, see Danon, Diaz-Guilera, Duch and Arenas 2005). The spectral partitioning method based on modularity (Newman 2006) is particularly appropriate for RCA. Unlike blockmodeling or hierarchical clustering, it does not require *a priori* assumptions about the number or size of subgroups. Rather the optimal number and size of divisions is achieved by maximizing the network's modularity, which is the number of edges falling within groups compared to that expected if the network were random, while maintaining its distribution of node degrees. Modularity maximization using eigenvalues exhibits particularly high performance, both in terms of modularity optimization and in its computational robustness[7]. It can be generalized to weighted networks by treating them as multigraphs, and is therefore applicable for RCA (see Newman 2004). Using modularity to find cohesive groups is also consistent with theories of schematic transmission because it takes into account the distribution of relationality measures for each individual respondent. Consider two respondents who are only weakly relationally overlapping with one another. The algorithm would weigh lower the significance of the edge between them the more each were overlapping with other respondents. In other words, modularity considers relational ties between respondents depending on the extent of their relational embeddedness.

[7] Because of its combinatorial complexity, an exhaustive search for an optimal division of a network into subgroups is practically impossible. Using eigenvalues allows reaching a partition in polynomial time.

Compared to other methods for analyzing multivariate data, RCA is specifically tailored to meet the challenges of finding relational structure both within and between observations. Overall, it is effective in detecting groups of relationally similar respondents which exhibit distinct pattern of covariance between variables. The robustness of RCA was tested in a series of simulations, in which it was used to detect relational structure in random data. It was found that RCA maintains reliable performance even with data whose underlying relational patterns are inconsistent and noisy[8]. In the next section, I demonstrate how RCA can be applied to survey data by analyzing American's musical tastes, as captured by the 1993 GSS.

Reexamining the Cultural Omnivore Thesis

Nowhere is the relational nature of culture more apparent than in how individuals acquire taste. As Bourdieu (1984) points out, the expression of taste is simultaneously a socially classifiable act and an act of social distinction. In other words, by declaring a taste one reproduces social structure by reclaiming one's position in social space while at the same time reinforcing the taxonomy that makes taste a social marker. Taste is the product of embodied social structure, not willful aesthetic sensitivity, that is developed incrementally through our experiences with the world around us, which themselves are shaped by the possibilities afforded by our social positions. Bourdieu's (1990) elaboration on the concept of habitus—the inter-subjective mechanism through which social structures are internalized as unconscious and naturalized dispositions—bears a strong affinity to schema theory (Strauss and Quinn 1997; D'Andrade 1995). It suggests that individuals' cultural preferences can be understood in terms of the shared

[8] See Appendix B for details.

understandings that produce their social significance, making musical taste an ideal candidate for exploration using RCA.

Mounting empirical evidence from the US, as well as other countries has persistently documented a shift in the orientation of high-status individuals towards an inclusive range of cultural preferences that traverses the traditional boundaries between high- and low-brow genres (Peterson 1992, 1997, 2005). It suggests that today, musical preferences function as social markers not through the distinction between elitist and popular musical forms but by differentiating between those with high and low levels of cultural tolerance. The rise of the so-called cultural omnivore seems inconsistent with Bourdieu's theory of cultural distinction, which expects to find exclusive correspondence between cultural taste and social position (Bryson 1996; Erickson 1996). But as Peterson and Kern (1996) argue, cultural omnivorousness does not altogether negate Bourdieu's theory; rather it introduces one's range of preferences as a new criterion for drawing symbolic boundaries. Put differently, it implies the emergence of a new cultural logic of distinction.

By cultural logic I mean the assumptions that people rely on in interpreting the motivations and intentions behind each other's actions (Enfield 2000). A distinctive cultural logic of distinction therefore suggests that people who employ it make consistent associations between cultural practices and the social performances they signify. Thus the emergence of a new cultural logic implies that the social meanings people once attributed to these practices have been collectively transformed.

Since the publication of Peterson and colleagues' first findings about cultural omnivorousness, a large number of studies have added refinements to the argument.

Following Bryson (1996), several have pointed attention to the mechanisms of exclusion that underlie omnivorousness, noting that an openness toward musical diversity often is accompanied by rejection of genres that are associated with marginalized social groups (Tampubolon 2008; Warde, Wright and Gayo-Cal 2008). Lizardo (2005) and Katz-Gerro (2002) similarly focus on people's practices of symbolic boundary formation, tying the logic of omnivorousness with that of post-national cosmopolitanism and post-Fordist identity politics. Other studies have looked for diversity within the patterns of omnivorousness, distinguishing between levels of musical tolerance (García-Álvarez, Katz-Gerro and López-Sintas 2007) and between high- and low-brow cultural omnivores (Peterson 2005).

What these studies share is an understanding of the relationship between social structure and taste predominantly through the prism of cultural diversity, implying that the logic of omnivorousness has supplanted the outmoded worldview that divides music between elite and mass genres. To be sure, since the 1970s, symbolic boundaries between genres have been eroding, while Americans have exhibited growing diversity in their musical preferences[9]. Yet to assume that within the space of two decades a shift had monolithically transformed cultural sensitivities seems to contradict what we know about the incremental, multi-directional and often compartmentalized way in which culture evolves (Swidler 1986; Collins 2004). In the heterogeneous and stratified American social landscape one would expect such institutional change to occur very slowly, if at all (DiMaggio 1987). Indeed whereas early studies emphasized a shift in highbrow consumers' tastes from exclusivity to omnivorousness, more recent work explores the

[9] However, this trend seems to have been reversed since the mid 1990s. See Peterson (2005) and García-Álvarez et al (2007).

juxtaposition of breadth of preferences with the old division between high- and low-brow tastes, finding that omnivores do not necessarily like highbrow music (Tampubolon 2008, García-Álvarez et al 2007). Yet by *a priori* presupposing how musical genres are hierarchically classified, authors of these studies effectively impose a framework of highbrow-versus-lowbrow on their findings.

But if Americans' cultural exclusiveness has changed in recent years, why should we not expect, or at least remain open to the possibility, that such change had also interacted with how genres are tacitly classified? Could the evolution of cultural sensitivity not have entailed that some genres that were once considered vulgar have been *de facto* canonized, whereas others were downgraded? Moreover, and perhaps most importantly, why should we expect the same logic of classification to be applied universally? Think of jazz as an example. On the one hand, jazz has been embraced and institutionalized as a form of high culture by music critics, academics and consequently the American public at large. Yet in part due to its African-American origins, jazz was associated with morally corrupting qualities throughout the early and mid twentieth century (Lopes 2002). Thus whereas those whose tastes are structured on a high-versus-low rationale might appreciate jazz as a marker of refined taste, others whose racial identity constitutes an important influence on their logic of classification may relate to jazz in accordance with their attitudes toward race. Consequently, different logics may prescribe different understandings of what types of music should be included in a particular category[10].

[10] As Lena and Peterson (2008) note, genre boundaries are brittle and often contested historically contingent social constructions. Consider mega pop stars like Mariah Carie or Beyoncé, both classified by Billboard magazine as R&B artists, as examples of mainstream singers who traverse genre boundaries.

The cultural omnivore thesis therefore calls for reexamination through a lens that is sensitive to the multiplicity of meanings that musical works elicit. Applying RCA to musical tastes is particularly appealing for three reasons. First, as Bourdieu (1984) notes, music is the quintessential social marker: musical tastes are not consciously acquired and expressed as means of social distinction, but are practical forms of enacting one's social standing. Even if the rankings of musical works are not as homologous with their consumers' social positions as Bourdieu's theory expects them to be, they still exhibit, as Bryson (1996) demonstrates, clear patterns of compatibility and opposition. Unlike some art forms, musical genres evoke strong feelings from detractors and enthusiasts alike (DiMaggio 1987). They are therefore easily operationalizable as scales that range from positive to negative attitudes, and that provide the basis for a relational analysis. Second, because RCA relies on the relations between the components that make up a certain domain, its efficacy is highly contingent on the exhaustiveness of the set of variables being analyzed. Compared to other lifestyle markers, the field of musical production is both bounded and institutionalized, making it amenable to RCA.

Finally, a variety of studies using musical tastes as a means to operationalize omnivorousness, some relying on the dataset used in this analysis, have been conducted in the past. Of those, a few specifically use latent-variable models and ordinal statistical methods to explore heterogeneity. García-Álvarez et al (2007) use longitudinal Latent Class Regressions, with breadth of musical preferences as their dependent variable, to demonstrate variability in levels of omnivorousness[11]. Tampubolon (2008) uses Latent

[11] Latent Class Regression is a powerful tool for detecting heterogeneity in the relationship between socio-demographic predictors and omnivorousness. But it also has its limitations: defining breadth of preferences as the outcome variable presupposes that it is the primary dimension along which respondents diverge. It is therefore not surprising that the authors find classes that are distinguishable by their level of

Class Analysis to examine patterns in the repertoires of respondents' musical likes and dislikes, and finds that omnivores can be divided by their low- and high-brow preferences[12]. Han (2003) uses Weighted MDS to demonstrate that individuals diverge not only in terms of their musical tastes, but also in the ways in which they differentiate between genres. He finds that the highly educated mainly discriminate against genres they strongly dislike, whereas those low on education reject all genres they do not strongly like[13]. Ultimately, however, neither study departs from the cultural omnivore framework. They all replicate both the assumption of omnivorousness as the primary axis of differentiation, and the conceptualization of musical hierarchy through a presupposed division into high- and low-brow tastes. Such imposed presuppositions do not allow them to examine the data beyond the basic conjectures of the cultural omnivore thesis.

Analysis

The data used for this analysis are drawn from the Culture Module of the 1993 General Social Survey. Respondents were asked to rate their preferences for seventeen

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omnivorousness. However such a theoretical imposition precludes the possibility that other axes of variability will be detected.

[12] Tampubolon's interesting findings, which demonstrate that different omnivore types mutually dislike the others' preferred genres, lead him to question the relationship between political, racial and musical tolerance suggested by Bryson (1996). Yet, on the face of it, a more appropriate conclusion would be that these findings unsettle the reliance of cultural omnivorousness theory on musical tolerance as its pivotal differentiating factor. It is difficult to conclude, however, to what extent this conclusion is warrented as the actual distributions, as opposed to model predictions, of group omnivorousness levels are not provided.

[13] These findings seem to tap the different logics of inclusion and exclusion that individuals employ as a function of their education. It is an attempt to integrate into one framework both the 'whats' and 'hows' of music classification. Though insightful about the mechanisms of cultural distinction, these results are nevertheless limited in three substantial ways: first, because educational attainment is used as a criterion for identifying different preference dimensions, and then correlated with these outcomes, the resulting patterns are self-referential. Second, only one socio-demographic—educational attainment—is used in the analysis. Han singles out those in possession of a graduate degree as high-status, but they constitute a mere 7 percent of the sample. And finally, the 'hows' are understood as the different distributions of preferences within genres, failing to take into account how these distributions relate to one another *across* genres.

musical genres on a five-point scale[14]. Respondents were also given the option to indicate that they do not know enough about a particular genre to have an opinion about it. Not knowing about a genre is not a meaningless answer, however; rather it indicates that the respondent is not sensitized to associate this type of music as a social marker. 'Don't know' responses were therefore imputed as 'having a mixed opinion' on a genre (corresponding to three on the five-point scale)[15]. However, the 53 respondents (which constitute 3.3 percent of the sample) who did not recognize more than six genres were removed from the sample due to their excessive musical illiteracy, leaving 1551 respondents[16].

The RCA procedure partitioned the data into three groups, representing 44.4%, 30.2% and 25.4% of the population respectively. Because RCA is likely to assign respondents with different tastes to the same group, examining group means can be misleading. Instead, since RCA increases the covariance between tastes within subgroups, looking at the correlations between variables is more informative. Correlations are normally summarized in matrix format. However graphical visualizations are more powerful in communicating the structure of such multidimensional data (DeJordy, Borgatti, Roussin and Halgin 2007). The correlation matrices of each subgroup are therefore illustrated as networks in Figure 3: each node

[14] Due to classificatory ambiguity, one genre was removed from the sample. See appendix D for a detailed description of the data.
[15] Using other imputations would defeat the purpose of RCA. Mean-based imputations might unjustifiably force clear positions where they do not exist, whereas regression-based imputations would artificially override sociodemographic heterogeneity.
[16] Despite its exceptional level of detail, this dataset ultimately relies on a coarse-grained classification of musical genres that is limited in its ability to make visible the ways in which social positions and musical tastes correspond. For example, one of the categories in the survey, defined as "Contemporary Pop/Rock", covers a large variety of subgenres that span from mainstream to alternative contemporary music, and that, presumably, have distinctive audiences. For brevity's sake, I refer to this category simply as 'pop' in the remainder of the analysis.

corresponds to one variable, and the edges connecting them to statistically significant correlations between variables[17]. Each node is also labeled by the value of its weighted clustering coefficient (CC)[18]. The CC measures the extent to which the neighbors of that node are also correlated with one another. A high CC indicates that its corresponding genre is part of a strongly connected cluster of genres, suggesting that it is pivotal in sustaining the interdependencies that produce the meaning structure it is part of.

The three groups exhibit very different structures of musical taste. In the first group, illustrated in panel A, there are no negative correlations between musical genres. Rather, all genres are positively correlated with one another, except for the four peripheral genres—country, rap, gospel and heavy metal—which are nevertheless still widely correlated with those in the center[19]. The narrow distribution of CC values suggests that this network presents no clear relations of precedence or opposition between genres. In other words, members of this class who like one genre also tend to like the rest. This does not mean, however, that they value all genres equally; rather, it suggests that they do not perceive the space of musical styles to be defined by one singular and explicit ranking. Such logic is perhaps best described as heterarchical: it exhibits relations of interdependence between musical preferences, which are amenable to multiple axes of distinction (Crumley 1995). A heterarchical logic fits well with the notion of cultural

[17] The Fruchtenman and Reingold spring embedding algorithm was used to spatially visualize network layouts.

[18] Only positive correlations are used for computing the CC. These are standardized by the maximal weight in the network, such that the coefficient values are proportional to level of clustering relative to the maximum possible (See Onnela et al 2005, eq. 9). Formally:

$$CC_i = \frac{2}{k_i(k_i - 1)} \sum_{j,k} \left(\tilde{w}_{ij} \tilde{w}_{jk} \tilde{w}_{ki} \right)^{\frac{1}{3}}$$

where w_{ij} is the correlation between nodes i and j, $\tilde{w}_{ij} = w_{ij} / \max(w_{ij})$, and k_i is node i's degree.

[19] These four genres are found by Bryson (1996) to be most likely disliked by those with large breadths of musical likes.

omnivorousness. It does not imply that omnivores like all music types indiscriminately, but that their rejection of cultural hierarchies allows for an openness to equally appreciate a broad variety of genres (Peterson and Kern 1996). Yet membership in this group does not necessarily imply a broad range of cultural preferences. While it includes the most omnivorous of all respondents—those who like all seventeen genres—this group also contains those who dislike all or most genres. It seems to be structured along a range that stretches from those with exceptionally broad tastes on the one side, to those with exceptionally narrow tastes on the other, who all similarly depart from a rationale that perceives some genres as inherently more valuable than others. Consequently, I refer to it as the *omnivore-v.-univore* group.

But the two remaining groups are not as compatible with the cultural omnivore thesis as the first one. The second group, depicted in panel B, is dominated by an old-fashioned logic that clearly divides between classical genres on the one hand, and popular genres on the other. This division does not perfectly correspond to traditional distinctions between high- and low-brow genres. For example, big band and folk music, neither of which is normally associated with elitism, are both strongly correlated with classical music. But the CC values indicate that classical music and opera, both quintessential forms of high culture, are the two most dominant genres in the set that also includes musicals, jazz and Latin music. Members of this *high-v.-low brow* group who either like or dislike these genres tend to dislike or like (respectively) country, pop, oldies, heavy metal and rap, all archetypal examples of lowbrow music, which are correlated with one another. Overall, roughly one third of Americans continue to perceive music through a

lens that sees an opposition between canonical, instrumental and traditional music on the one side, and popular contemporary music on the other.

Similarly, the third group also exhibits an unambiguous opposition between two sets of musical genres. Yet this dichotomy is different from the conventional distinction between high and low culture. As depicted in panel C, one side of the correlation network is dominated by a cluster that is centered on gospel, and which also consists of bluegrass, country, folk, and easy listening, all, except for the latter, musical forms that are associated with American folklore. Big band and musicals are also loosely coupled with this cluster. On the other side of the fault line, heavy metal, jazz, pop, reggae and rap, and to a lesser degree Latin, oldies and blues, form another set of musical genres that are characterized by their contemporary appeal. This polarity resonates with a tension between, on the on hand, local identity that is rooted in white American tradition, and an urban culture that celebrates racial and ethnic diversity. Unsurprisingly, classical music and opera, both musical forms that, framed in terms of the *urban-v.-smalltown America* opposition, constitute a canon that transcends locality and time, are the only two genres that are neither opposed nor exclusively correlated with either set. Both also have the two lowest clustering coefficients, suggesting that they are marginal for the construction of meaning in this group. Unlike in the Hi-Low group, these two genres do not figure prominently as delineators of opposing musical repertoires, nor are they defiantly positioned alongside popular genres in a manner that challenges the traditional distinction between high and low culture.

Mapping Social and Musical Spaces

The three cultural logics identified by RCA exhibit different orderings of musical genres. However if these also function as logics of social distinction—that is, if they provide principles of musical evaluation that demarcate different social groups—we should expect them to diverge sociodemographically. But because each group contains individuals who may be on different sides of the cultural divisions it is structured on, examining their average sociodemographic profiles may be misleading. Rather, if each group is characterized by different understandings of the social significances of various musical genres, we should expect musical preferences and sociodemographic attributes to be correlated differently with one another in each group.

What sociodemographic dimensions warrant examination? Bourdieu's framework of cultural distinction focuses on the link between one's class position and cultural capital. It expects to find that musical preferences diverge along axes of socioeconomic status such as education, occupational prestige and income. More recent theories, which point to the growing salience of non-class-based identities in post-industrial societies, suggest that cultural consumption may be associated with other forms of social status. Studies on cultural omnivorousness focus on age as a significant source of cultural cleavage, as younger cohorts supposedly reject the rigid artistic sensibilities of their parents' generations (Peterson and Kern 1996). Others have suggested that gendered, regional, ethnic and religious identities have all become increasingly important in shaping taste (Katz-Gerro 2002; Lizardo 2005). Variables that tap these different social dimensions were used in the analysis that follows[20].

[20] Locality size, which measures the size of the locality in which the respondents resides, is used as a continuous measure of the level of urbanism of the respondent's residence. Race intolerance is measured

I examine correlations between sociodemographic attributes and taste in two ways. First, I look at the relationship within each group between individual and additive scales of genre preferences on the one hand, and sociodemographic attributes on the other. These are presented as fitted models in Figure 4. The five scales that are used in this part of the analysis correspond to the patterns of genre clusterings that cohere in the three groups identified by RCA, each traversing standard musical classifications. These include highbrow and popular scales which emerge from the Hi-Low group, traditional and contemporary scales which emerge from the Urban-Town group, and a scale comprised of rap and heavy metal, two genres that are marginalized in the Omni-Univore group (for scale compositions see Figure 4). The opposing correlates between pairs of taste and social attributes across groups—for example, the correlation between education and heavy metal which is positive in the Urban-Town group, negative in the Hi-Low group, and insignificant in the Omni-Univore group—imply that each group is defined by different understandings of the social significances of musical genres.

Second, I explore how these attributes are correlated with the differences between pairs of genres in each group, which I refer to as delta correlations. Looking at differences between genres, as opposed to examining individual genres or their additive scales, simultaneously captures the appreciation of one genre and rejection of the other. This taps the underlying relational mechanism of cultural distinction, whereby the meaning of aesthetic preferences as social markers emerges from the ways in which they relate to one another. The delta correlations between age, opera and country, for example, are instructive. While in the Hi-Low group, opera is increasingly appreciated over

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using an additive scale of five questions about racial attitudes. It is identical to the scale used by Bryson (1996). For a detailed description of the sociodemographic variables used in this analysis, see Appendix D.

country as a function of age, in the Urban-Town group, the opposite is the case. Performing one's age role is achieved by simultaneously valuing and devaluing the opposite genres in each group. In the Omni-Univore group, however, age is not associated with a preference for either genre, suggesting either that that group's logic of distinction does not mark its practitioners' ages, or that the distinction between these two genres is not pivotal in producing it[21].

Delta correlations highlight the variety of contextual social meanings that musical genres take. A close look at two genres that are particularly amenable to different social interpretations—jazz and pop—demonstrates the different social polarities that each group is structured on (Figure 5). In the Hi-Low group, jazz seems to signify its fans' socioeconomic status and maturity, as it is increasingly appreciated over country and pop as a function of education, occupational prestige and age. In the Urban-Town group on the other hand, where younger people are more likely to be urban, secular, non-white and non-southerners, jazz's infusion with these racial, regional and religious identities becomes visible when compared with a variety of traditional genres.

In contrast to jazz, pop is associated with low socioeconomic status in the Hi-Low group. When compared to rap, for example, the extent to which pop is devalued by educated members of the Hi-Low group becomes visible: while in both other groups people tend to increasingly appreciate pop over rap as they become more educated, in the Hi-Low group, where pop is understood in terms of its opposition to higher musical forms, it is neither liked more nor less compared to rap, irrespective of education. But being antithetical to jazz in the Hi-Low group does not imply that pop is similarly

[21] Pearson correlation coefficients were computed for age and the difference opera-country in each group. Significance was determined for alpha = 0.05. In the Omni-Univore group the coefficient was found insignificant, in the Hi-Low group it is 0.354, and in the Urban-Town group -0.314.

oppositional to it in the Urban-Town group; rather, like jazz, it seems to denote a variety of identities that are rejected by white, religious, small-town southerners. The different social meanings signified by pop in each group become even more apparent when considering the average delta correlation between pop and other genres (Figure 6). In the Omni-Univore group, pop is increasingly appreciated more than other genres as a function of education, occupational prestige and income, suggesting that in this group it is a symbol of high socioeconomic status. In fact, with the exception of classical music, as this group's respondents' income increases so do they tend to like pop more than they do every other genre. Unlike in the Urban-Town group, however, liking pop more than other genres is also associated in this group with racial intolerance and being white. Whites in this group prefer pop over all genres with black roots indiscriminately, whether rap, jazz, blues or gospel.

Considered together, the distributions and correlations between social attributes and musical preferences uncover the different and intersecting axes of distinction along which the three groups are structured, and how those are marked by musical taste. Figure 7, which compares the extent to which each sociodemographic variable explains the variance in deltas between all genres in each group, provides an overview of these differentiating axes. It demonstrates that the Hi-Low group is distinctive in its polarization by status, mainly in the form occupational prestige, but not by income. That this group is also differentiated by gender is in line with previous studies that found that women tend to specialize in household status-building by consuming high culture (Collins 1992; García-Álvarez et al 2007). The Urban-Town group, on the other hand, exhibits a logic of musical distinction that predominantly marks racial, religious and

regional identities. The social divisions in the Omni-Univore group seem far more nuanced. This does not necessarily imply that they do not exist, but that because members of this group are defined by their relatively egalitarian musical preferences, these divisions are not as pronounced as they are in other groups. In fact the differences between musical preferences in this group are explained by income more than they are in the two other groups. This seems to suggest that while those high on professional and educational attainment, but not so much on wealth, display their cultural capital by clinging to old musical hierarchies, those with economic capital but more modest educational success gravitate toward more heterarchical forms of musical distinction.

Where are the Omnivores?

On the whole, the RCA analysis draws an intricate picture of three competing ways in which people understand the social significance of music: one, based on a contemporary adaptation of the old division between high- and low-brow music, distinguishes people by age and status; another, differentiates between contemporary and traditional genres as a means to signify age as well as religious, racial and regional identities; and yet another, accounting for almost 45 percent of the population, adheres to a more undiscriminating logic that nevertheless allows its practitioners to display their economic capital.

What do these results tell us about high-status Americans' supposed relinquishing of cultural snobbism in favor of inclusiveness? The absence of hierarchy in the musical tastes of members of the Omni-Univore group implies an egalitarian logic which is congruent with cultural omnivorousness. But the boxplots in Figure 8 demonstrate that the two are not one and the same: members of the Omni-Univore group are, by average,

only modestly more omnivorous than their peers in the two other groups. Examining the dispersion of individual preferences in each group, on the other hand, makes visible how the Omni-Univore group differs from the other two. The mean difference between musical preferences, which is depicted in panel B, measures the extent to which an individual has an unequal appreciation of musical genres[22]. The low mean difference in the Omni-Univore group suggests that its members have a more indiscriminate appreciation of musical genres than their peers do, whether they equally like or dislike most genres. The correlations presented in Figure 9 demonstrate that what distinguishes this group is not so much how the social positions of its members are reflected by their levels of omnivorousness, but how they correspond to the extent to which their preferences are equitable[23]. While in the two other groups the tendency to make cultural distinctions is mostly related to age, in the Omni-Univore group it is a reflection of one's high occupational status, economic capital, and white racial identity.

Overall, the analysis presented here does not undermine the assertion that music consumers diverge in the breadths of their cultural preferences in socially significant ways. The positive relationship between education and omnivorousness, for example, is consistent across all three groups. But these results add important qualifications to the cultural omnivore thesis. The evidence for the existence of three, competing logics of musical distinction, suggests that at least 55 percent of Americans do not perceive musical consumption as defined primarily by how broad one's preferences are.

[22] The mean difference is a measure of statistical dispersion that equals the expected absolute difference between two random variables drawn from a distribution. It is an alternative measure to the standard deviation, which is not calculated in respect to the mean. It tends to give more weight to small deviations.
[23] Similar results were obtained when using other operationalizations of omnivorousness that are in line with Peterson and Kern's (1996) conceptualization of omnivores as individuals who consume both highbrow and non-highbrow culture.

Examining the actual composition of individuals' repertoires of musical tastes is therefore more informative than merely looking at their range. The remaining 45 percent exhibit a pattern of musical preferences that ranges from exceptionally strong omnivorousness to strong univorousness. But the divergences in their sociodemographic profiles become most pronounced when examining the level of egalitarianism in their preferences, not its breadth. The correlation, in this group, between high status and discriminating taste, as well as the association between income, racist tendencies, and rejection of music with black roots, further undermine the supposed connection between omnivorousness and tolerance.

Because the data used here do not vary across time, they ultimately tell us very little about whether omnivorousness, however conceptualized, is a relatively recent cultural phenomenon, as proponents of the omnivore thesis have argued. Notwithstanding, the results of this analysis nevertheless highlight three important insights that are often overlooked in studies of social symbolism of cultural taste. First, they demonstrate that practical classification systems emerge from the multiple relationships between significances that consumers ascribe to musical genres, and do not necessarily correspond to generally accepted taxonomies. The canonical distinction between high-, middle- and low-brow culture is not reflected in any of the classifications that emerge from the three groups identified by RCA, not even the Hi-Low group where, for example, folk music is associated with classical music and opera. Relying on *a priori* assumptions about the rankings and similarities between musical genres might therefore obscure the ways in which music and people are matched in intricate systems of classification. By refraining

from such impositions, RCA succeeds in identifying the coexistence of different classification systems which are normally overlooked.

Second, the divergent correlates between sociodemographic attributes and musical preferences in each group demonstrate that the same musical genre may carry different meanings in different social contexts. Jazz, for example, is understood as a symbol of socioeconomic status in the Hi-Low group, whereas in the Urban-Town group it marks racial tolerance, secularism and urbanism. Thus its rejection in the former group appears to be related to class identity, whereas in the latter to regional and racial identities. Similarly, while pop is associated with racial tolerance in the Urban-Town group, it is a signifier of intolerance in the Omni-Univore group. Such multivocality requires a methodological approach that does not presuppose that the relationship between sociodemographic attributes and cultural practice is homogenous within a given population.

Finally, the results of this study also demonstrate why addressing homogeneity by decomposing the population into predefined sociodemographically homogenous groups cannot fully account for the complex interplay between social position and cultural taste. As the delta correlations demonstrate, pop simultaneously marks high socioeconomic status in the Omni-Univore group and low socioeconomic status in the Hi-Low group. While in the former a performance of high status entails liking both pop and classical music, in the latter it entails liking classical music but disliking pop. The same set of sociodemographic variables therefore has different predictive effects on musical taste in each group. If we were to model these effects using conventional regression analysis over the sample as a whole, these two opposing trends would have offset one another.

Moreover, examining the correlations between the various sociodemographic variables in each group highlights that high-status individuals in these two groups are distinguishable by age: whereas younger educated and high-income individuals tend toward cultural heterarchy that embraces both popular and classical music as a means to perform their class, older individuals cling to more old-fashioned classifications that continue to discriminate between high and popular culture. But because each group contains individuals of all ages—in the Hi-Low group, younger people reject music that is normally labeled highbrow—modeling such interactive complexity using conventional regression analysis would have been practically impossible. Taking into account both the associations between genres—in this particular example classical music and pop—as well the similarities between individuals, allows RCA to uncover these complex patterns without making *a priori* assumptions about how heterogeneity is explained by sociodemographics.

Conclusion

Mapping shared understandings, and the social profiles of those who hold them, is a key undertaking for those set to unpack the elusive construct we call 'culture'. But because cultural objects—like music—often elicit different meanings in different contexts and for different people, this is not a simple task. Sociologists of culture have long argued that the meanings that social actors attribute to symbols and actions emerge from the multiple associations they make between them, and aggregate into coherent structures of relevance and opposition through interpersonal interaction (Mohr and White 2008). Uncovering these structures therefore requires a relational approach that simultaneously looks for patterns of similarity and opposition within and between

individuals' attitudes. But conventional statistical methods are not attuned to meeting this challenge. Consequently, studies that rely on such methods for analyzing multivariate cultural data are often forced to (1) draw on *a priori* assumptions about how cultural objects are classified, (2) overlook ideational heterogeneity by presupposing that the relationship between social attributes and cultural interpretations is consistent across individuals, and (3) essentialize certain social dimensions as defining the boundaries between different cultural groups.

Studies on cultural omnivorousness, despite their substantial contribution to our understanding of the social significance of taste, are, by and large, no exception. By examining data from a relational perspective, RCA obviates the limiting assumptions they mostly rely on. This allows it do discover musical classification systems that defy outmoded divisions between high- and low-brow culture; reevaluate divergent musical preferences of individuals not only as different flavors of omnivorousness but as parallel logics of social distinction; and highlight how various social dimensions like age, education and urbanism interact in complex ways to produce mappings between sociodemographic attributes and musical preferences. As these results problematize some of the findings and assumptions of previous studies, they also ultimately put into question the utility of omnivorousness as an analytical concept.

The analysis presented in this paper is primarily intended as a test case that demonstrates the usefulness of RCA. It does so by showing that the three groups detected by it differ in their patterns of association between musical preferences, and in the relationships between these patterns and their practitioners' social backgrounds. The different and often opposing correlations between social attributes and musical

preferences within each group, such as the different social significances that liking pop carries, underscore the distinct shared understandings that each group is founded on. Compared to other works on cultural omnivorousness, this analysis provides a more nuanced and complex account of the variety of ways by which social status and musical taste correspond to one another.

Unlike other methods that look for groups of likeminded people, RCA compares actors not by the similarities in their beliefs, but on the basis of their shared understandings of the mutual relevance and opposition between beliefs. This makes it particularly suitable for complex sociological problems in which the outcome is not a singular variable but rather a set of interdependent variables. For example, knowing that someone likes pop music tells us very little about them; only by understanding how this preference relates to other symbolic behaviors can others extrapolate its social significance. RCA might also be applicable to problems outside the scope of sociology *per se*, such as analyzing complex structures of political opinion or consumer behavior. In fact, it can be extended to virtually any problem that requires dealing with heterogeneity by identifying groups that vary with respect to systematic patterns of relationships. These may include, for example, problems of equifinality in the patterns of change over time in the behaviors of people, firms or financial institutions.

Overall, RCA is a powerful inductive tool for the analysis of culture. But like any method, it has its limitations. It does not free its users from the need to carefully, and in a theoretically informed manner, select and operationalize their variables. Because relationality is computed by comparing all pairs of differences between variables, it is highly sensitive to the boundary conditions defining the domain that it measures.

Moreover, because the boundaries between groups depend on the different schematic representations that individuals use, they are never clear-cut as our theoretical impositions expect them to be. While some individuals occupy corners of the belief space that are defined by distinct cultural logics, others might be located closer to the intersections between them. RCA can therefore be extended to use partitioning algorithms that provide likelihoods of belongingness to a group, rather than binary assignments to them (see for example Schweinberger and Snijders 2003; Handcock, Raftery and Tantrum 2007). More generally, future research would benefit from further investigations into the merits of various techniques for partitioning the relationality matrix, as well as the criteria for distinguishing between significant and insignificant values that are used to generate the relationality network.

Reexamining cultural omnivorousness with RCA makes visible the complex nonlinearities that connect social structure and its symbolic production. Given the paucity of systematic data on musical preferences in the US from periods earlier than the 1970s, it is difficult to gauge to what extent the cultural omnivore is a unique product of post-sixties cultural sensitivities. But assuming that a cultural shift has indeed occurred in the manner described by the omnivore theory, the coexistence of different logics of distinction demonstrated in this analysis suggests that culture can evolve in several directions at once: in face of changes in the institutional environment, some (the Hi-Low group) cling to established symbolic hierarchies, some (the Urban-Town group) redraw their boundaries, whereas others (the Omni-Univore group) redefine them. It also demonstrates that the same bounded field of social activity can lend itself to different interpretations that rely on competing understandings, and that correspond in complex

ways to their practitioners' social backgrounds. Ultimately, in thinking about the incremental process of cultural evolution, relationality alerts us not to how cultural transmission moulds individual attitudes but how it fine-tunes relations between these attitudes to tacitly produce complex structures that collectively aggregate into shared understandings.

Appendix A: Determining Significant Relationality

Relationality is theoretically bounded by -1 and 1. Values that are close to zero are therefore of less significance than those on either extreme of this range. But relationality is affected by the structure and distributions of the data, complicating the determination of significance in two ways: (1) for multivariate categorical data, the lower bound of relationality is dependent on the number of categories per variable, and (2) depending on the actual distribution of values, average relationality may be substantially different from zero.

The first complication is a result of the mathematical properties of relationality. When using categorical or non-continuous ordinal data, the number of possible distances between variable values is finite. Because relationality compares the difference in distances between all pairs of variables across two observations, if the number of possible distances is finite, so is the number of their potential differences. Two observations have -1 relationality only in the case that all pairs of variables have the exact opposite difference between observations. If the number of variables being compared is greater than the number of categories per variable, however, it becomes combinatorially impossible for this condition to be met. Under such circumstances, relationality will be bounded by 1 and a lower bound greater than -1. Consequently, it will, by average, be greater than zero. As the number of categories increases, the average relationality between random observations grows asymptotically closer to zero.

Panel A of Figure A-1 summarizes the mean and standard deviation for relationality produced for random data, as a function of the number of categories per variable. These results were produced by computer-generated simulations, for data containing ten

variables. As this figure suggests, in cases that rely on ordinal data where the lower relationality bound is greater than -1, the distribution of relationality scores is skewed above zero. To address this bias, RCA centers the values in the relationality matrix by the mean relationality.

Drawing on the Central Limit Theorem, relationality for random multivariate categorical data should be normally distributed. Mean relationality and its standard deviation for random data can therefore be useful in determining which of the weights in the relationality network produced by RCA are statistically insignificant. But sampled social data is very rarely normally distributed around the categorical mid-range, making comparisons to random simulations less useful. Panel B compares the frequencies of relationality values in the sample used in this analysis and in simulated random data using the same number of variables and categories. Because there are only five categories and seventeen variables, relationality is strongly skewed above zero in both cases. The dashed lines represent the 95% confidence interval based on the mean and standard deviation of the simulated data. The observed relationality is, by average, significantly higher than expected if the data were random. Using the simulated distribution as a benchmark for determining significance would result in retaining 37.01% of the edges in the relationality network, keeping it substantially dense. Alternatively, an estimate of the distribution of relationality in the population can be reached using a bootstrapped sample of the observed data. Such a procedure, based on 10,000 resamples, resulted in an estimate of the mean at 0.4354 and the standard deviation at 0.1617. These values were used to determine significance at the alpha=0.05 level.

Appendix B: Performance

In order to test the robustness of RCA a series of computer-generated simulations were performed. Datasets of 90 observations comprised of 9 variables, each on a categorical scale of 1 to 10, were generated (these sizes are arbitrary; results similar to those reported here were produced for datasets of different sizes). These datasets were divided into three equally sized pairs of subsets of observations, such that the subsets in each pair correspond to opposing relational patterns. All 15 observations in each subset follow the same relational pattern. The relationalities between these patterns are presented in Table B-1. These are the values we would expect to receive between observations that fully adhere to the relational pattern of each subset. The pairs are sequentially ordered, such that the first and third have maximal relational dissimilarity, while the second pair has strong but not complete dissimilarity. RCA analyses for these datasets had 100% success rate in assigning observations to their subset correctly.

Additional RCA analyses were performed to test RCA's resilience. Noise was introduced by randomly shifting the values in each observation away from its subset's pattern. Figure B-1 provides an example of three observations from one subset, and the mean shift in value generated for each of them. Observation C, for example, has a mean shift of 1.33, meaning that by average each variable was shifted by more than one category, whereas observation A remained consistent with the subset's pattern.

All in all, 20,000 simulated datasets were produced, with large variance in the mean shift in values (variance was randomly generated from a normal distribution with a random standard deviation ranging from 0.1 to 2). RCA analyses were performed for each dataset, and assignments to subgroups were compared to original subset assignment.

A typical relationality network and its partition, as produced from a simulated dataset, are presented in Figure B-2. In this particular instance, the mean average shift for each observation was 0.474. RCA had a 97.8% success rate in correctly assigning observations to subgroups. As shown in the network diagram, only observations that had a high average shift (greater than 1.75) were assigned incorrectly by RCA. The insets in Figure B-2 show the relational patterns of these two observations. As demonstrated, they diverged substantially from their original patterns, to the extent that they are more consistent with the patterns of the groups to which they were assigned.

Overall, RCA is extremely efficient in identifying relationally similar subsets of observations under noisy conditions (which arguably correspond to real-life datasets). Figure B-3 presents the fraction of observations correctly assigned to their original subset, as a function of their average variable shift (Panel A), and the mean variable shift in their network as a whole (Panel B). Even for networks in which the mean shift is 1, that is, in which by average all values were shifted randomly by 1 unit, RCA successfully classifies 90.59% of cases. Across all simulations, observations in which all values were shifted by 1 unit were correctly assigned in more than 97% of cases. Only for observations whose values are shifted by average 1.75 units or more from their original relational pattern does the performance of RCA begin to substantially deteriorate, but these observations presumably bear very little resemblance to their original form.

Appendix C: RCA Compared to Other Methods

A variety of methods that can be used for detecting relational structure in multivariate data are available for analysts. Of those, two related families of methods that offer an alternative to RCA warrant attention. Latent variable models such as Factor Analysis and Latent Class Analysis (LCA) explain variability by detecting latent, unobserved factors or classes. However unlike RCA, these methods seek to maximize independence between observed variables when controlling for the latent variables. Put differently, rather than parsing groups of respondents whose attitudes follow similar relational patterns, they find groups of individuals that have similar attitudes. But, as discussed above, people whose positions are close do not necessarily employ the same rationale in constructing them. Moreover, in looking for heterogeneity, latent variable models treat each observed variable independently, and do not take into consideration the multiple relationships between them.

The results of a factor analysis and a latent class analysis of the data are summarized in Figure C-1. The factor analysis produced three factors that explain 54.6%, 31.29% and 17.46% of variance respectively. They are visualized in Panel A. The factor loadings of the first two factors roughly correspond to the variable correlations in the Hi-Low and Urban-Town groups detected by RCA. But the third factor, which exhibits an opposition between Americana and classical music, bears no resemblance to the Omni-Univore group, the largest detected by RCA. LCA, on the other hand, as the boxplots in panel B demonstrate, divides the sample into five classes that are significantly different in their level of omnivorousness. The number of classes was determined using Bayes Information Criterion (BIC). Group memberships in the two analyses were determined by

the factor estimates for each observation produced by the factor analysis, and by posterior likelihoods of class memberships produced by the latent class analysis. Overall, the cross-tabulations between factor values and groups detected by LCA on the one hand, and RCA group assignments on the other (panels C and D), demonstrate that the first two methods and RCA provide different perspectives of analysis.

A second family of methods falls in the category of statistical ordination, and includes Correspondence Analysis (CA), Principal Component Analysis (PCA) and Multidimensional Scaling (MDS). All these methods are normally used as exploratory tools to visualize multivariate data, usually in two-dimensional space. Bourdieu's (1984) influential study of cultural tastes in 1960s France, which is particularly relevant to the cultural omnivore thesis discussed here, is an example of the application of CA to the study of culture. At their core, ordination methods all decompose the data relationally. However the first two, which use eigenvectors for this purpose, rely on the covariance matrix, thus overlooking relational structure within observations. MDS is perhaps the most 'relational' of these methods. It is a popular tool for mapping relations in cultural data (Mohr 1998). MDS receives a matrix of dissimilarity between components as input, and reduces it to a lower dimensional space. However it often uses Euclidean distance as a measure of dissimilarity, which, as demonstrated earlier, is insensitive to relational similarities within observations. Theoretically, MDS could use a relationality matrix as its input. Yet even then, because it merely reduces the data to fewer dimensions, other procedures would be necessary to partition the data into groups for the purpose of modeling and inference.

Finally, alternative techniques can be used to either measure relational similarity between two observations, or to partition the relationality matrix into subgroups. A plausible alternative for relationality for measuring relational similarity is row correlation. But row correlation is sensitive to the variance of preferences within observations, overweighing similarities between observations with high internal variance. People often employ different scales, but still follow similar preferential patterns, in which case row correlation would be insensitive to their similarities.

Cluster analysis is a family of methods that, using a distance matrix assign observations into groups. Two techniques, hierarchical clustering and K-means clustering, are often used in multivariate analysis and both could be theoretically used to partition the relationality matrix into groups instead of the spectral partitioning algorithm. But these methods rely either on *a-posteriori* (hierarchical clustering) or *a-priori* (K-means) determinations of the number of groups. The modularity-based spectral algorithm, on the other hand, determines the number of groups by optimizing the overall modularity. Other advantages of this method are discussed above. However cluster analysis as well as other methods may have advantages over the spectral algorithm used in this analysis, which require further examination.

Appendix D: Variables

Respondents were asked to state their preference for seventeen musical genres, on a scale ranging from 'Like very much', to 'Like it', 'Mixed feelings', 'Dislike it', and 'Dislike very much'. The genres include: (1) Big Band/Swing, (2) Bluegrass, (3) Country/Western, (4) Blues or Rhythm and Blues, (5) Broadway Musicals/Show tunes, (6) Classical Music: symphony and chamber, (7) Folk Music, (8) Gospel Music, (9) Jazz, (10) Latin/Mariachi/Salsa, (11) Mood/Easy Listening, (12) Opera, (13) Rap Music, (14) Reggae, (15) Contemporary Pop/Rock, (16) Oldies Rock and (17) Heavy Metal. An additional genre, New age/Space music was, together with Reggae, the most unrecognized genre: 306 (19.1%) respondents either did not know much about it or refused to respond. Unlike Reggae, however, New Age/Space is very vaguely defined (see Bryson 1996). Consequently, it was removed from the analysis. 'Don't know' responses were recoded as 'mixed feelings' if the respondent did not provide this answer for more than six of the seventeen genres. The distributions are presented in Figure D-1.

Previous studies have pointed to a variety of sociodemographic determinants of cultural taste. Of these, education, income and occupational prestige have been particularly emphasized as shaping cultural repertoires (Bourdieu 1984). Peterson's cultural omnivore framework has similarly focused on cohort effects, whereas new refinements to the theory have pointed attention to a variety of regional, racial and gendered identities as related to breadth of cultural preferences. Consequently, the following variables are used as control variables in the correlations reported in this analysis (their distributions are reported in table D-1):

Age	Respondent's age. For presentational purposes only this is reported in tens of years (i.e, an increase in one unit corresponds to ten years of age).
Education	Measured in years.
Occupational Prestige	Based on the 2 digit Hodge, Siegel and Rossi occupational prestige score for Census Bureau industrial classifications.
Income	Family income, logarithmically transformed. The original variable, which is divided into ordinal categories, was transformed by the midpoint of each range.
Locality Size	Population of the locality in which respondent resides, logarithmically transformed.
Religious Services Attendance	How often does the respondent attend religious serviced, on a nine-point scale ranging form never to more than once a week.
Racist	An additive scale of questions on racial attitudes, which include: (1) "Would you yourself have any objection to sending your children to a school where more than half of the children are Black?" (2) "In general, do you favor or oppose the busing of Black and White school children from one school district to another?" (3) "On average Blacks have worse jobs, income, and housing than White people. Do you think these differences are . . . mainly due to discrimination?" (4) ". . . because most Blacks don't have the chance for education that it takes to rise out of poverty?" (5) ". . . because most Blacks just don't have the motivation or will power to pull themselves out of poverty?".
Female	Dummy for respondent's gender
White	Dummy for respondent's race, dichotomized as white/non-white
Southern	Dummy for whether the respondent resides in one of the states defines by the Census Bureau as southern.

Figures

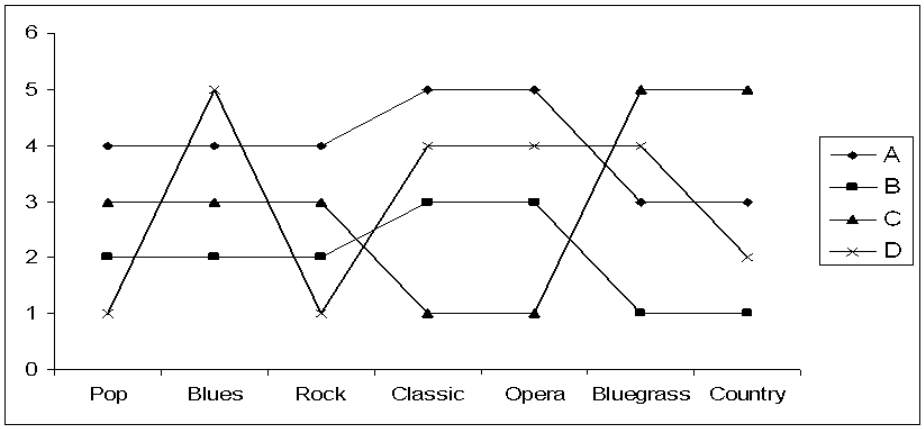


Figure 1 Visualization of the musical tastes of four hypothetical respondents. The Y axis is scaled from 'strongly dislike' (1) to 'strongly like' (5)

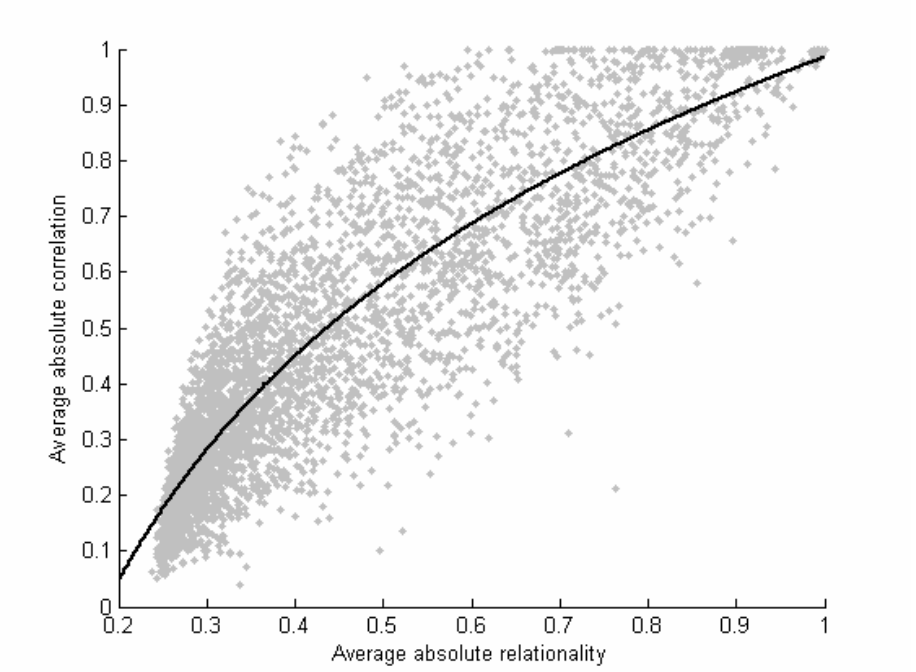
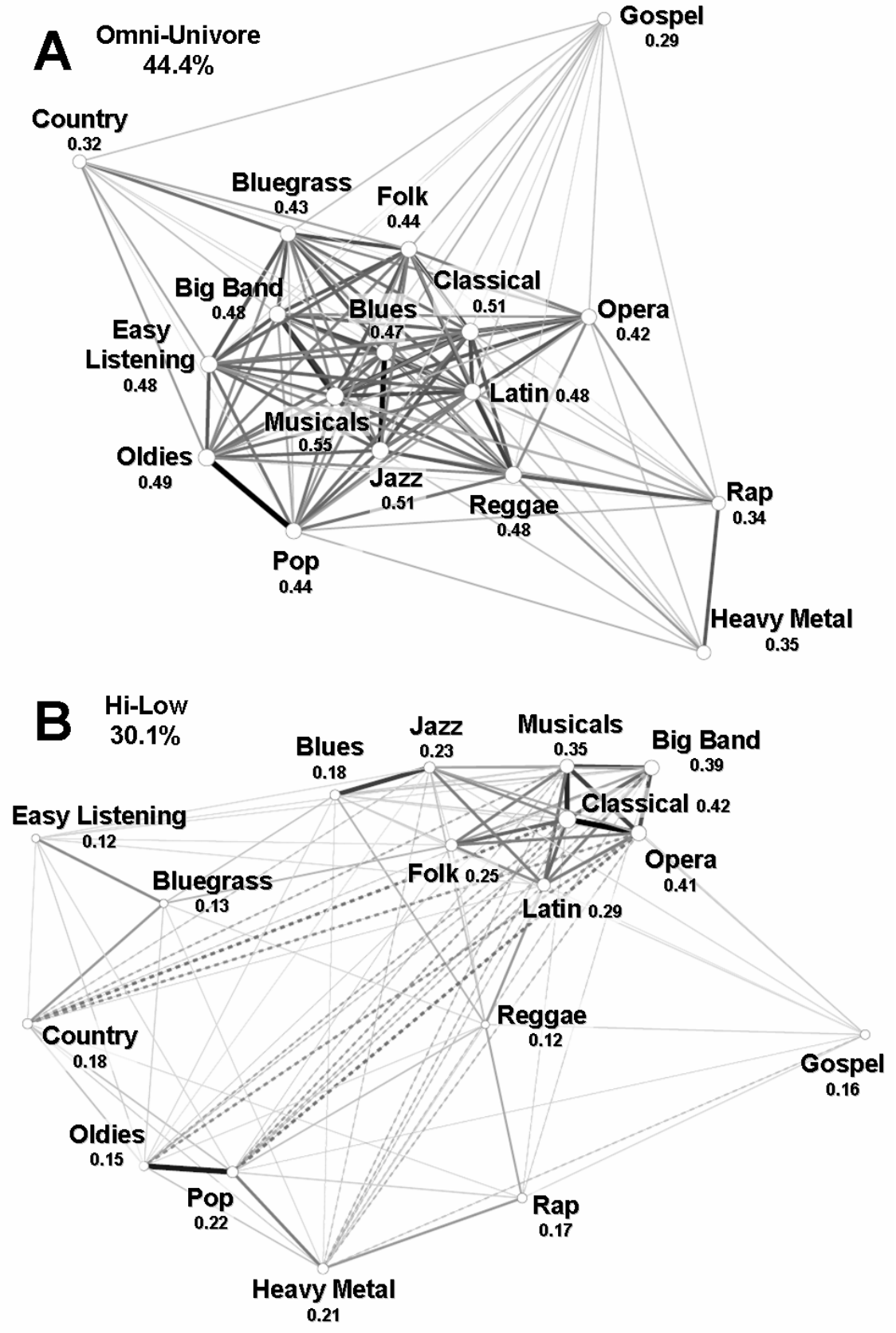


Figure 2 Correlation between variables as a function of relationality between respondents in simulated data


A
Omni-Univore
44.4%
Gospel
0.29
Country
0.32
Bluegrass
0.43
Folk
0.44
Big Band
0.48
Classical
0.51
Blues
0.47
Opera
0.42
Easy
Listening
0.48
Latin 0.48
Musicals
0.55
Oldies
0.49
Jazz
0.51
Reggae
0.48
Rap
0.34
Pop
0.44
Heavy Metal
0.35
B
Hi-Low
30.1%
Blues
0.18
Jazz
0.23
Musicals
0.35
Big Band
0.39
Classical 0.42
Easy Listening
0.12
Opera
0.41
Folk 0.25
Bluegrass
0.13
Latin 0.29
Reggae
0.12
Country
0.18
Gospel
0.16
Oldies
0.15
Pop
0.22
Rap
0.17
Heavy Metal
0.21

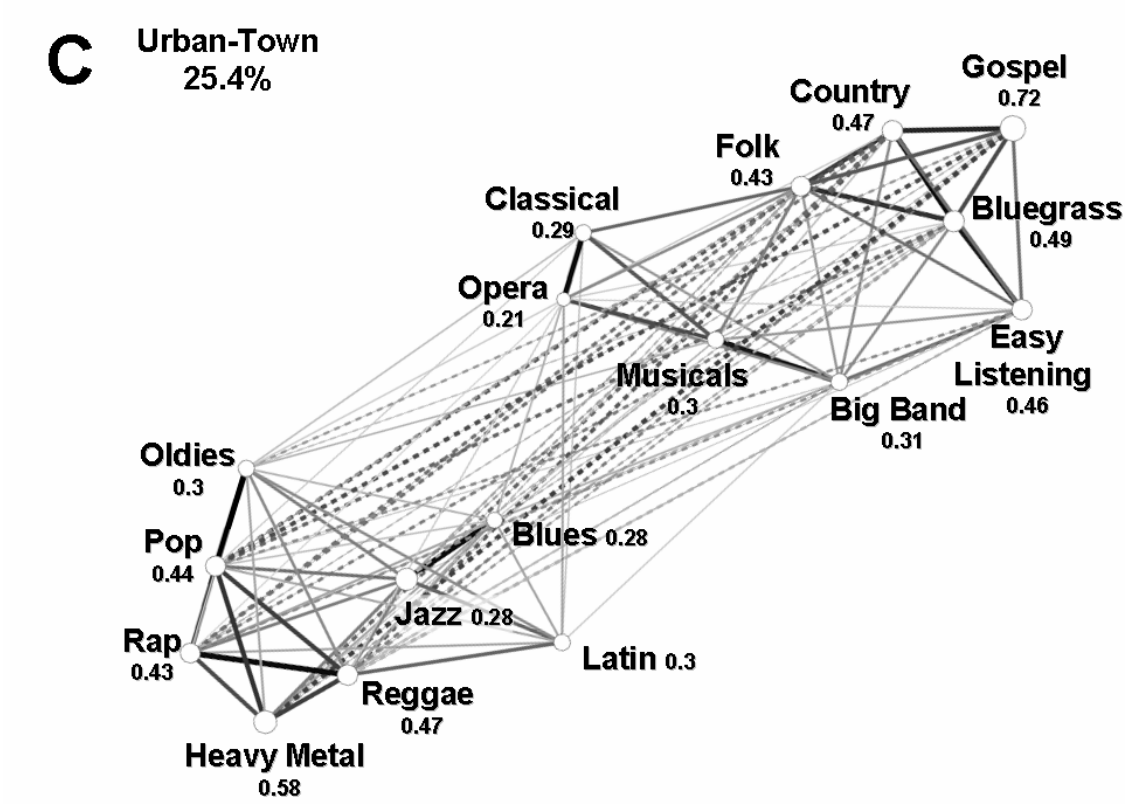


Figure 3 Networks of correlations between genres in each of the groups detected by RCA. Each panel corresponds to one group. Each node corresponds to one genre variable, and each line connecting two nodes to the correlation between them, only if significant at alpha = 0.05. Numbers and node sizes represent the weighted clustering coefficient of each node, standardized by the maximal weight in the network. Solid lines represent positive correlations, and dashed lines negative correlations. Line shades and widths are proportional to the strength of the correlation.

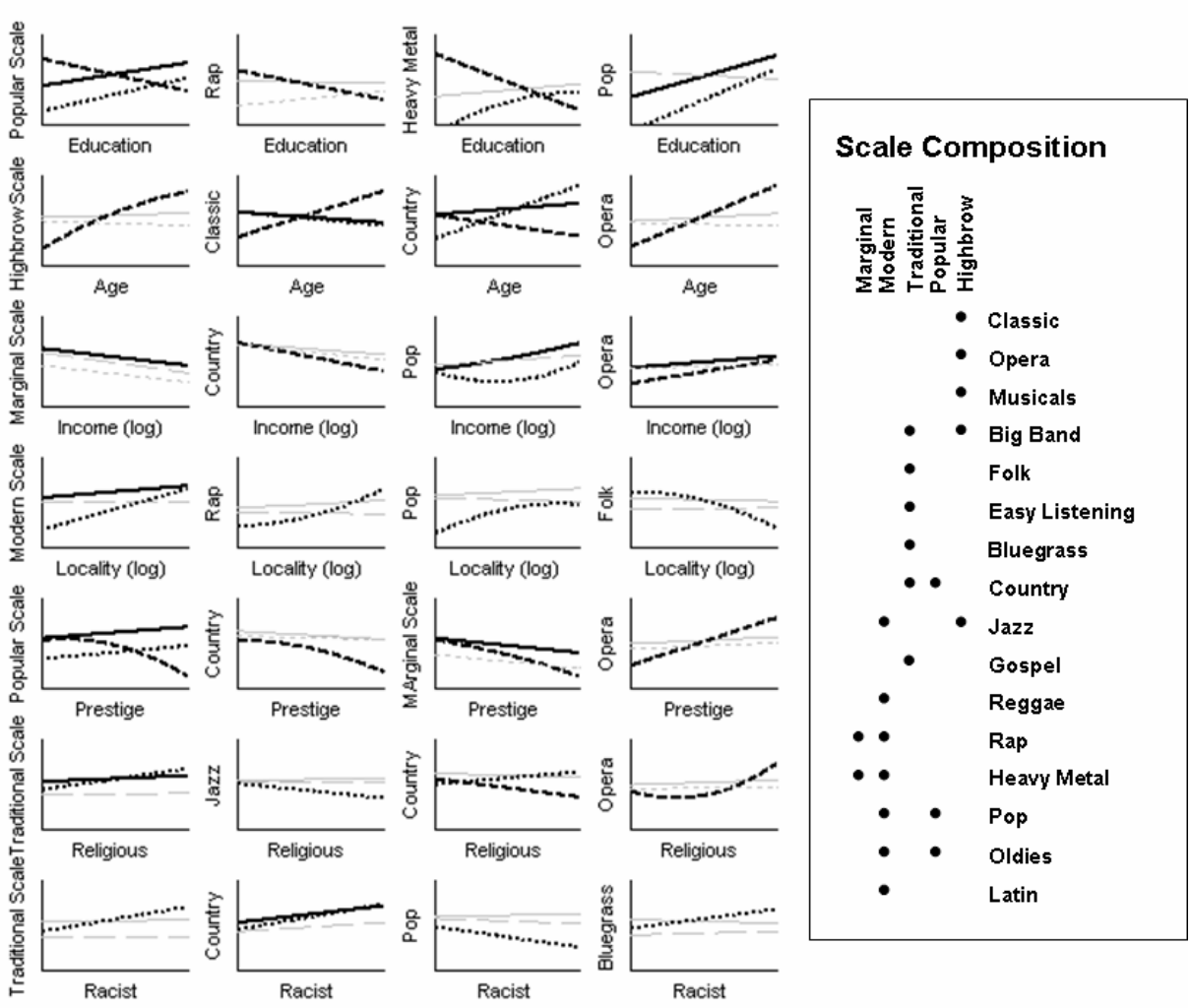


Figure 4 Fitted models representing the relationship between sociodemographic variables, on the X axis, and musical genre preferences, on the Y axis, by RCA group. The solid line represents the Omni-Univore group, the dashed line the Hi-Low group, and the dotted line the Urban-Town group. Grayed lines represent insignificant (alpha = 0.05) relationships.

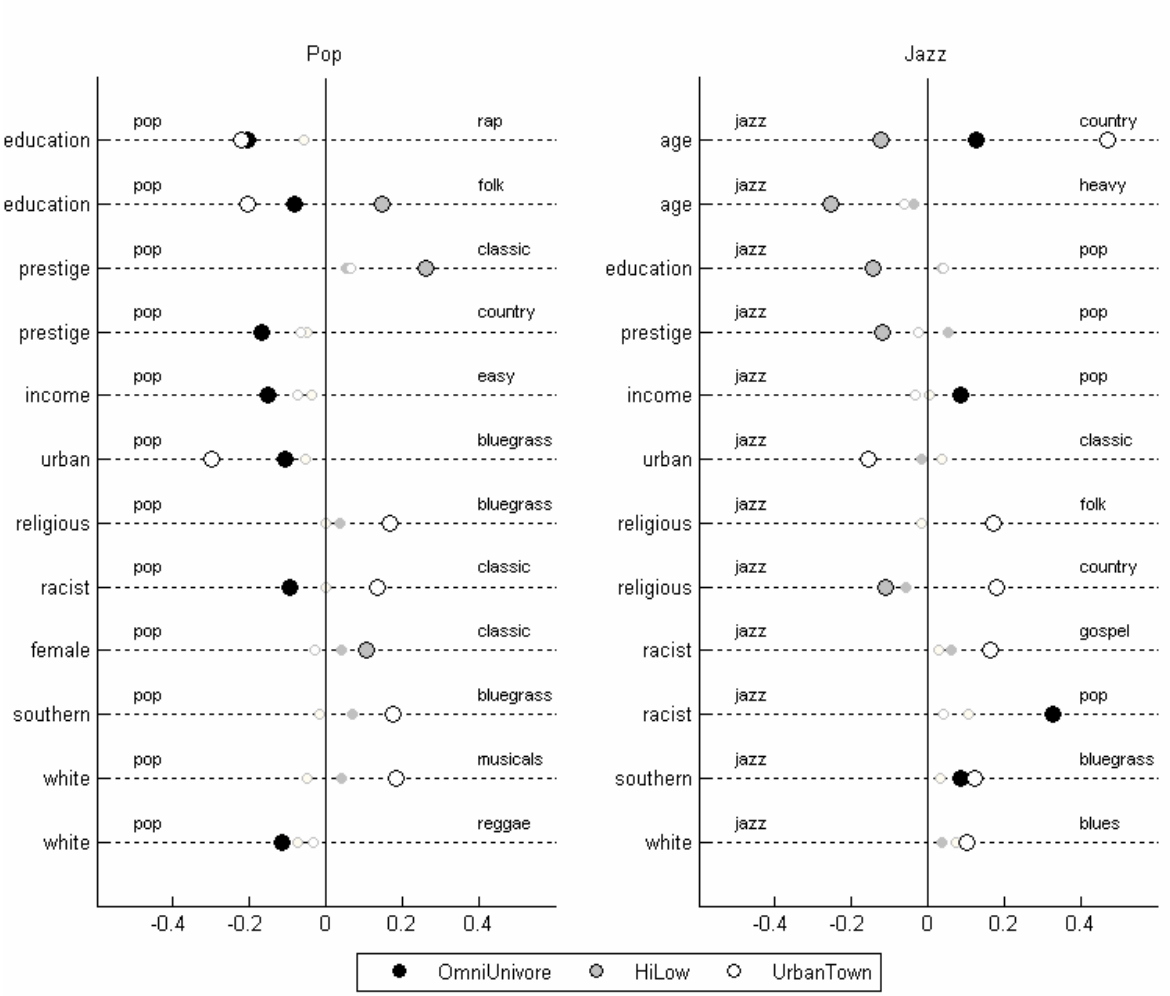


Figure 5 Delta correlations for Jazz and Pop, disaggregated by RCA group. Each row represents one correlation between a sociodemographic variable and the delta between two genre preferences. Large circles signify a significant correlation (for alpha=0.05), such that the difference between the two genres increases in the direction of the genre to which the circle is closer as a function of an increase in the sociodemographic variable. Insignificant correlations are represented by smaller grayed circles. For example, classical music is increasingly appreciated over pop in the HiLow group as a function of occupational prestige, whereas in the two other groups this relationship is statistically insignificant.

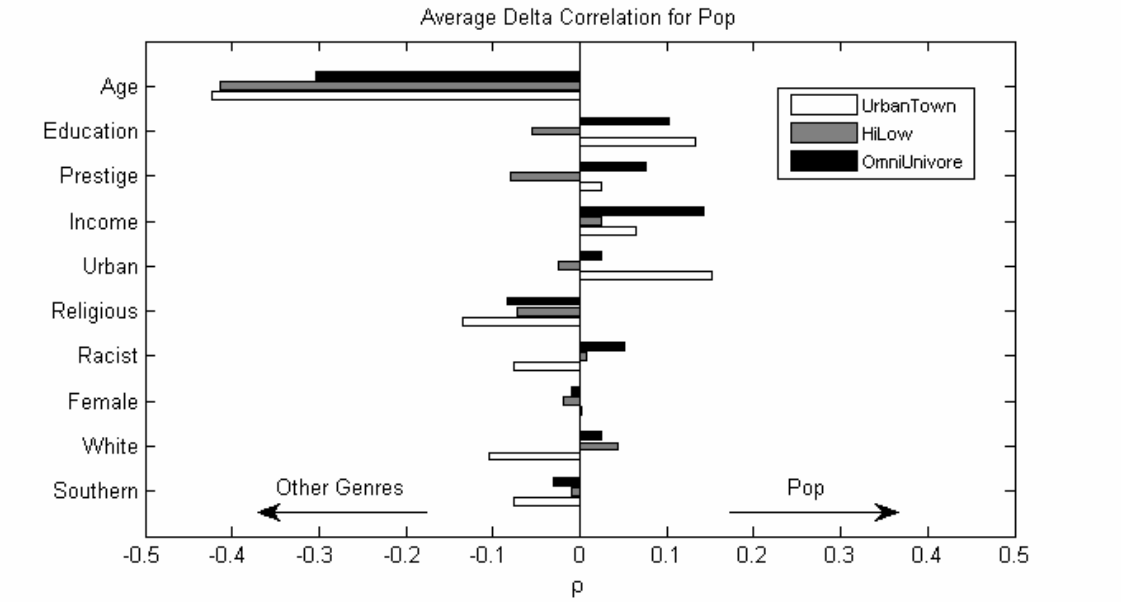


Figure 6 Average delta correlations for pop, disaggregated by RCA group. Each bar represents the average delta correlation between the sociodemographic variable on the Y axis, and the difference between pop and all other genres. For example, income is most strongly associated with a preference for pop over other genres in the Omni-Univore group. By average, the correlation between income (logged) and the difference between pop and any other genre is 0.17 in this group.

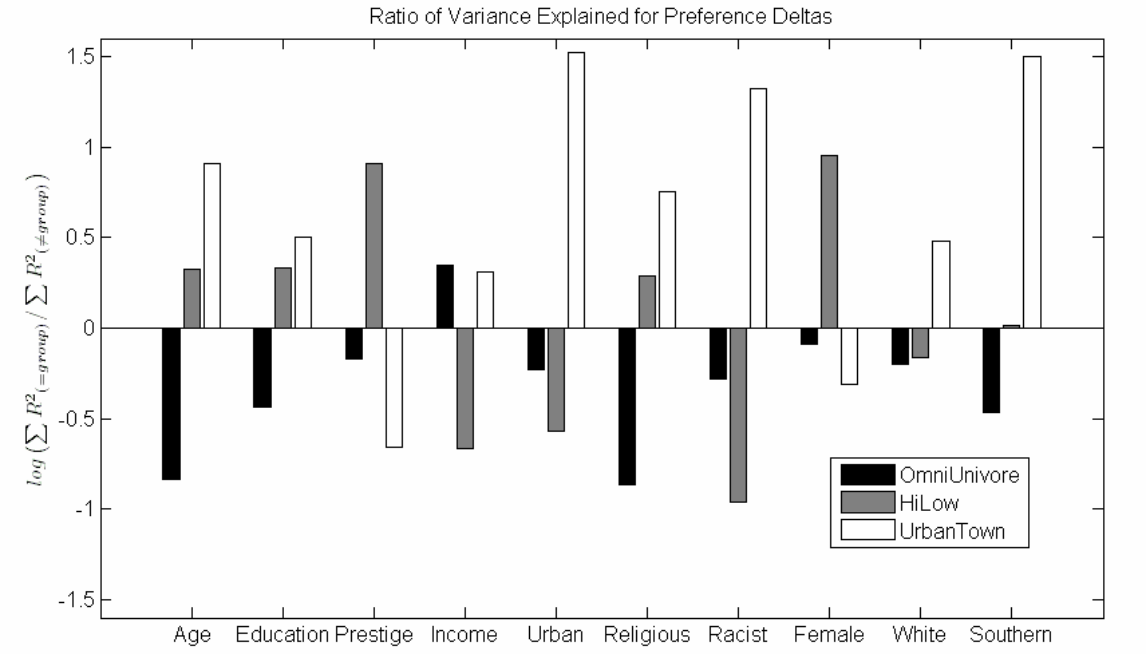


Figure 7 Ratios (logged) between the variance in genre preference deltas explained by sociodemographic attributes in each RCA group, and the variance explained by these attributes in the two other groups. For example, the variance in the difference between all pairs of genre preferences is explained by occupational prestige in the Hi-Low group far more than it is in the two other groups.

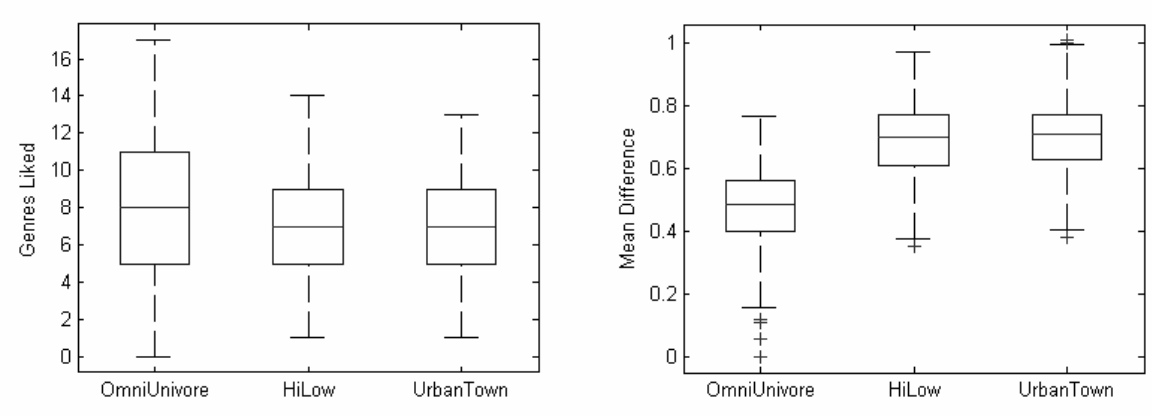


Figure 8 Distributions of numbers of genres liked and the mean difference between genre preferences, by RCA group

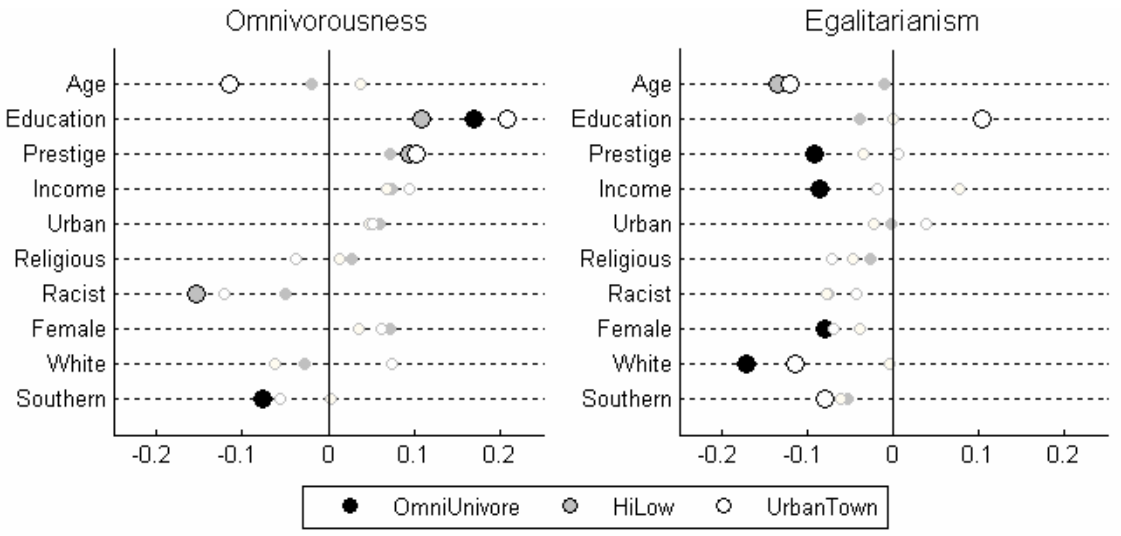


Figure 9 Pearson correlation coefficients for omnivorousness, measured as number of genres liked, and egalitarianism, measured as the opposite of the mean difference between genre preferences, disaggregated by RCA group. Each row represents correlations with one sociodemographic. Large circles signify a significant correlation (for alpha=0.05). Insignificant correlations are represented by smaller grayed circles.

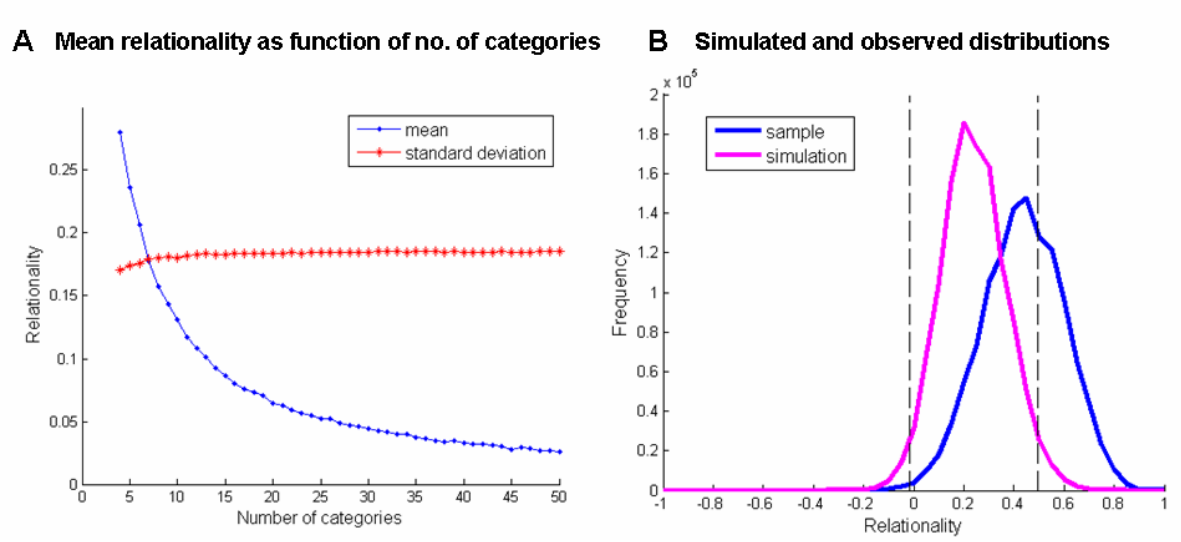


Figure A-1 Relationality Distribution. Panel A plots the mean relationality and its standard deviation as a function of the number of categories in each variable in simulated data. Panel B compares the distributions of relationally in the observed data and in random simulations.

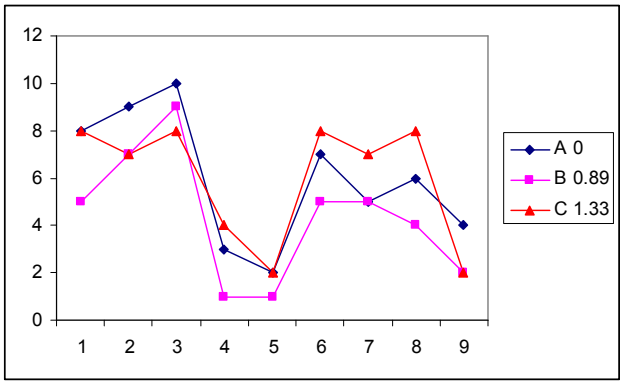


Figure B-1 Example of three observations from subset #1, and the mean shift in value generated by the performance simulations. The mean shifts are provided in the legend.

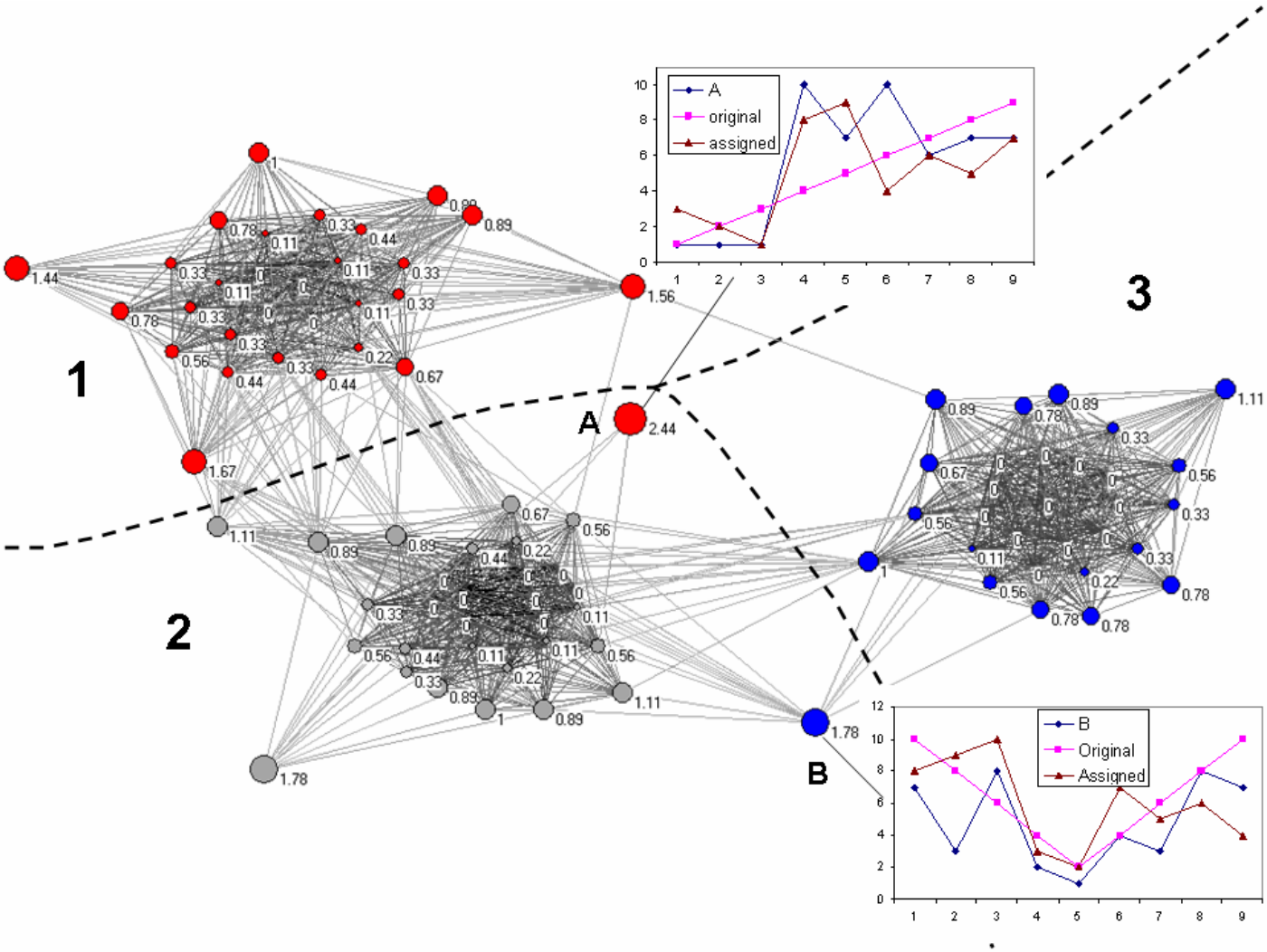


Figure B-2 RCA relationality network and its partition for a typical simulated dataset. Each node represents one observation. Node colors represent original subset assignments. Node labels and sizes correspond to the average shift from subgroup pattern. The dotted line outlines the partition produced by RCA. The insets compare the two wrongly assigned observations with their original and assigned group patterns.

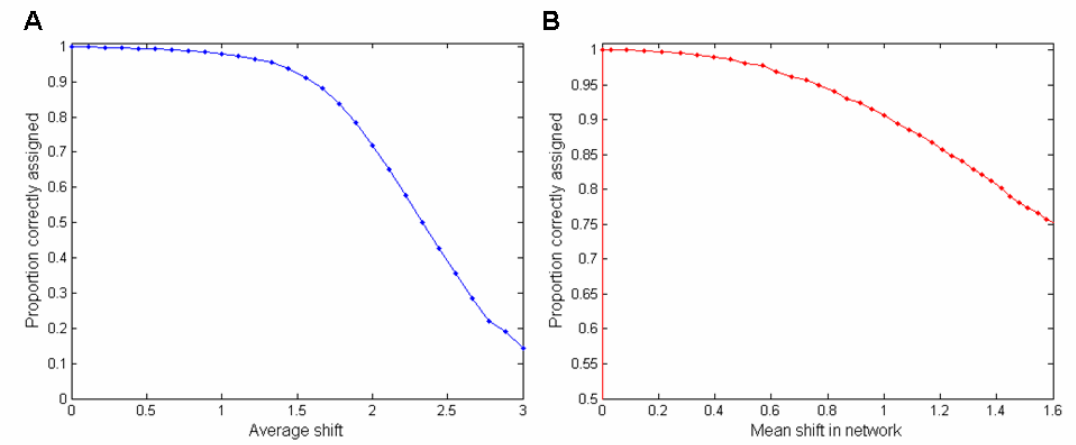


Figure B-3 RCA performance under noise: Panel A plots RCA success in assigning individual observations as a function of the average shift in value. Panel B plots RCA success as a function of the mean shift in the network as a whole.

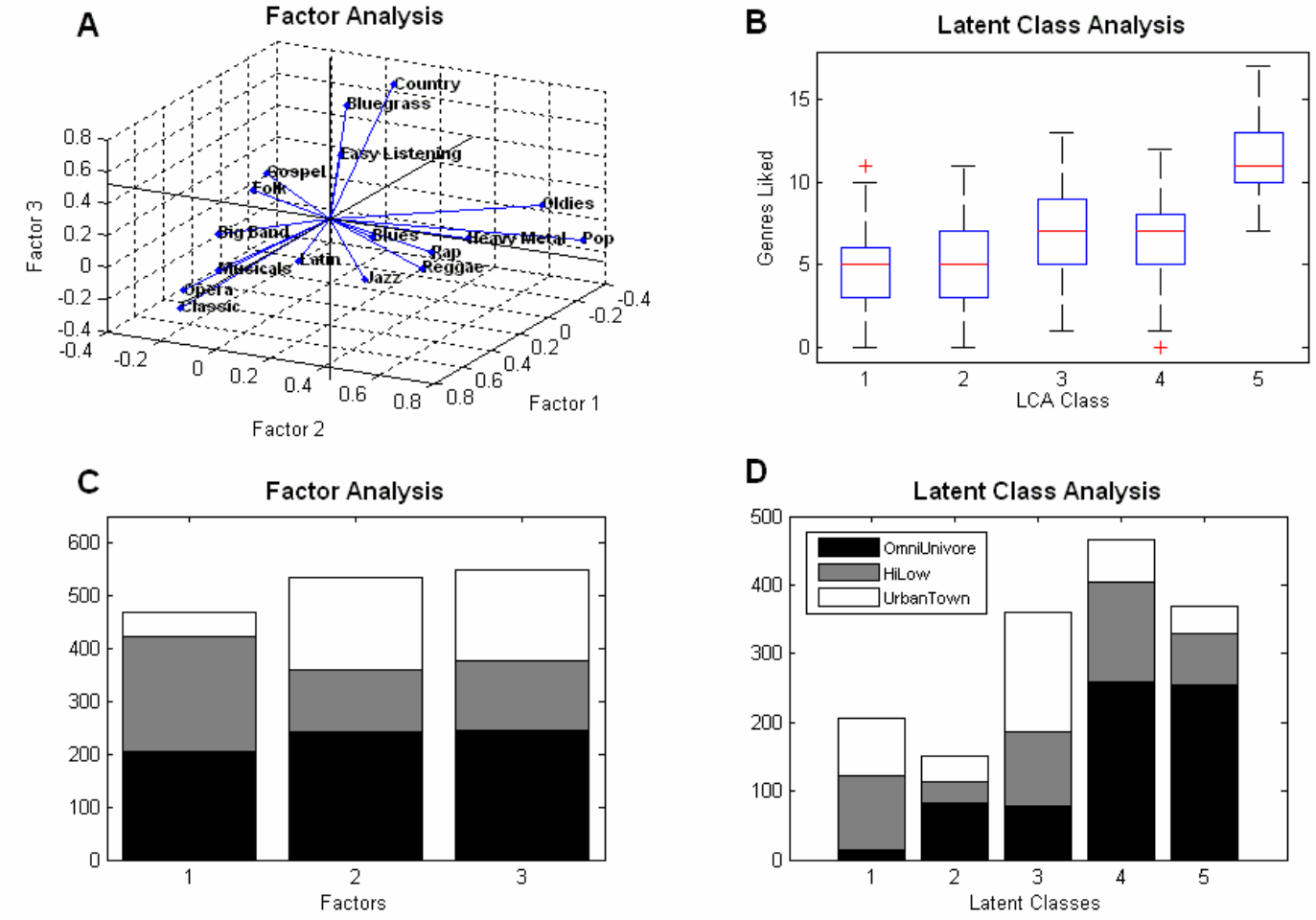


Figure C-1 Results of factor and latent class analyses compared with those produced by RCA. Panel A visualizes observed variable loadings for each of the factors resulting from the factor analysis. Panel B describes omnivorousness distribution (measured as number of genres liked) by latent classes found by the latent class analysis. Panels C and D present cross-tabulations between greatest factor value (C) or latent class assignment (D) and RCA group assignments.

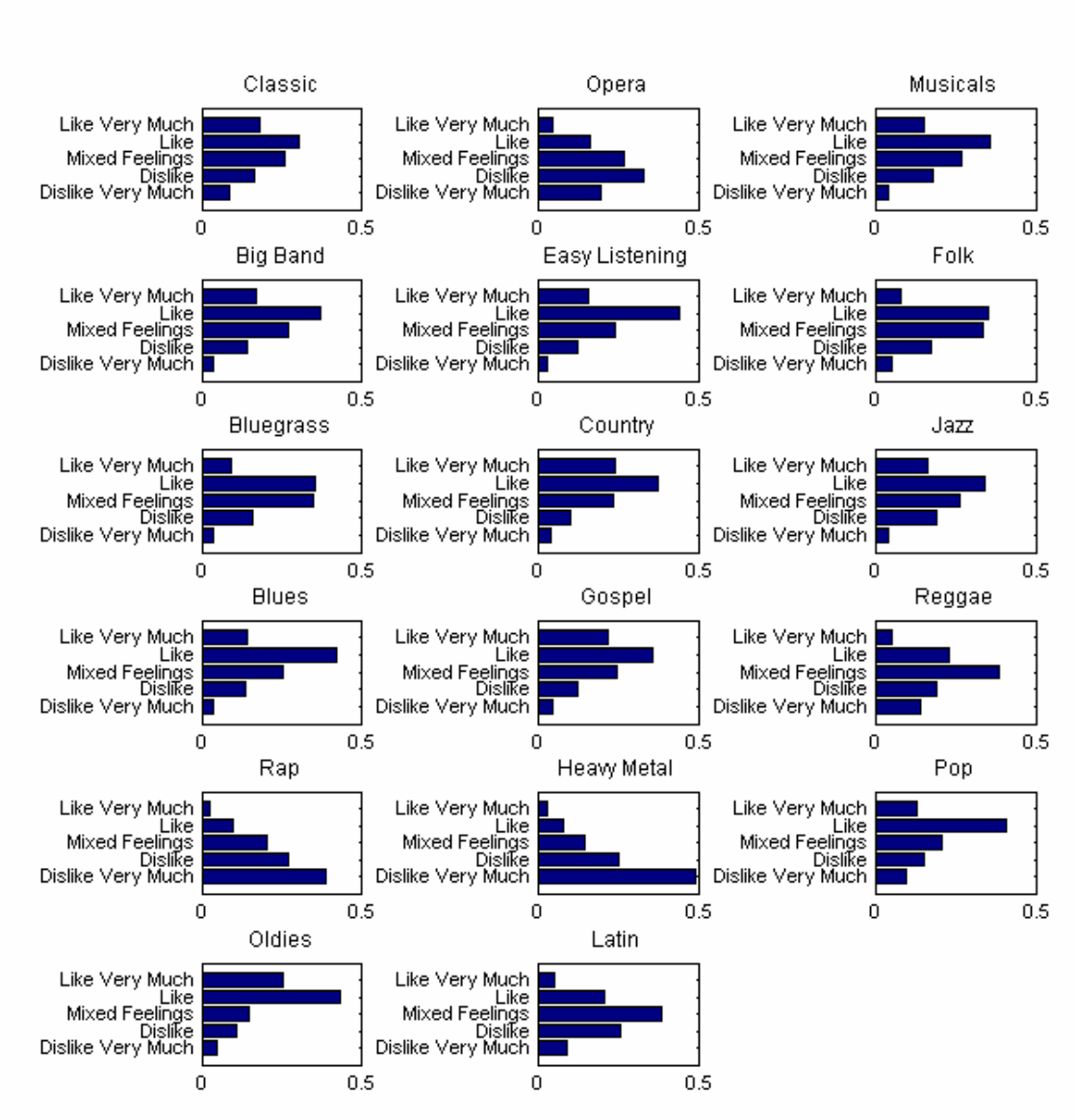


Figure D-1 Distributions of musical preferences by genre

Tables

Respondents	Euclidean	Relationality
A and B	0.5000	1.0000
A and C	0.6196	-0.2857
A and D	0.4532	0.1905
B and C	0.6196	-0.2857
B and D	0.4532	0.1905
C and D	0.5976	0.0714

Table 1 Euclidean distance and relationality between all pairs of observations depicted in Figure 1. Euclidean distance is standardized by the maximum possible

	Subset 1	Subset 2	Subset 3	Subset 4	Subset 5	Subset 6
Subset 1	1	-1	0.0494	0.0494	0.3457	0.0802
Subset 2	-1	1	0.0494	0.0494	0.0802	0.3457
Subset 3	0.0494	0.0494	1	-0.7778	-0.0617	0.5864
Subset 4	0.0494	0.0494	-0.7778	1	0.5864	-0.0617
Subset 5	0.3457	0.0802	-0.0617	0.5864	1	-0.5
Subset 6	0.0802	0.3457	0.5864	-0.0617	-0.5	1

Table B-2 Relationality between observations in different subsets generated by performance simulations

Variable	Mean	Std. Dev.
Age	45.81	17.12
Education	13.11	3.03
Occupational Prestige	41.30	15.90
Income	36742	26851
Locality Size	361	1232
Religious Service Attendance	3.8835	2.7465
Racial Intolerance	2.2365	1.4157
Female	0.5725	0.4949
White	0.8427	0.3642
Southern	0.3443	0.4753

Table D-1 summary statistics for sociodemographic variables

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