Poetics 60 (2017) 76–89

Contents lists available at ScienceDirect

Poetics

journal homepage: www.elsevier.com/locate/poetic

Research note

Music classification, genres, and taste patterns: A ground-up network analysis on the clustering of artist preferences

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ARTICLE INFO

Article history:
Received 9 August 2016
Accepted 30 August 2016
Available online 9 September 2016

Keywords:
Cultural omnivore
Music taste
Social network analysis
Two-mode network
Infinite relational model

ABSTRACT

This article reflects on the use of predetermined genre lists to measure patterns in music taste and, more specifically, cultural omnivorousness. The use of a predetermined array of genres assumes that music genres are rigid and stable concepts, whereas in reality genre boundaries continually emerge, evolve, and disappear. Inspired by Lamont's (2010) call to study classification systems 'from the ground up', we present an alternative strategy to measure patterns of music taste using an open question about artist preferences. We build a two-mode network of artists and respondents to identify clusters of respondents that have similar relationships to the same set of artists. Our results show that research using measurements of cultural omnivorousness based on genre preferences might be hampered, as it misses important subdivisions within genres and is not able to capture respondents who combine specific aspects within and across music genres.

1. Introduction

In the early 1990s, Peterson (1992) and Peterson and Kern (1996) introduced the concept of the cultural omnivore, when he discovered a shift in American music taste from a highbrow-lowbrow distinction to a contrast between high-status omnivores–who combine elite and popular culture–and lower-status univores (Bourdieu, 1984; Peterson, 1992). Since then, the cultural omnivore concept has been widely debated in cultural sociology. During the last two decades, researchers around the world have shown the prevalence of cultural omnivorousness in a variety of social settings (e.g. Peterson & Kern, 1996; Peterson, 2005; Stichele & Laermans, 2006; van Eijck & Lievens, 2008; van Eijck, 2001). Some researchers have focused on 'volume' measurements, based on a score or a scale that counts the number of genres a person likes in order to quantify the 'voraciousness' of a cultural consumer (e.g. Bryson, 1996). Others have used a 'compositional' approach, which concentrates on specific combinations of music genres (e.g. van Eijck & Lievens, 2008).

Although there is substantial variety in the operationalization of the cultural omnivore in quantitative research, the use of genres as a starting point seems to be beyond discussion. Researchers use the liking of genres, often combined with a dimension-reduction technique such as latent class analysis or factor analysis, to construct cultural omnivorousness measurements in terms of volume or composition of taste. Nevertheless, the use of broad music genre preferences was questioned by Bourdieu (1984), who insisted that music cannot simply be categorized into cultural genres, as there will be

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http://dx.doi.org/10.1016/j.poetic.2016.08.004
0304-422X/

differences in the specific types of musical works that are part of these genres. Recent quantitative and qualitative work on boundary drawing around music genres has confirmed this proposition. Genre boundaries are 'fuzzy' and the hidden dimensions in genre categories are often overlooked by researchers (e.g. Beer & Taylor, 2013; Beer, 2013; Savage & Gayo, 2011; Savage, 2006; Sonnett, 2016; van Venrooij, 2009).

In this paper, we argue why research on the cultural omnivore based on preferences for a predefined list of music genres might start off on the wrong foot. Inspired by Lamont's call to study classification systems 'from the ground up' (Lamont, 2010; p. 132), we offer an alternative strategy to measure music taste and taste patterns by using an open question about artist preferences. We build on existing knowledge in social network analysis to construct a two-mode network of people and music artists–conforming to the duality between people and cultural items–and we use state-of-the-art network clustering techniques to identify clusters of people who have similar relationships to the same set of artists (Breiger, 1974; Dimaggio, 1987). By using this bottom-up approach, taste patterns emerge from the data, an ad hoc list of genres becomes redundant, and we obtain a more detailed measurement of music taste patterns. In a last step, we link this new typology of taste patterns to known correlates of cultural preferences in order to compare our results with existing research on the prevalence of the cultural omnivore and the sociodemographic context.

2. Theory

2.1. "Classification as culture" (Lena & Peterson, 2008)

Classifications of music genres are central in quantitative research on cultural omnivorousness (Beer, 2013). Cultural researchers typically use a predetermined array of genres to measure differentiation in music taste. However, there is no validated and widely-accepted measurement instrument for music taste. Research differs greatly, in the number and labeling of genres and the instructions for respondents (Peterson, 2005). For example, Chan and Goldthorpe (2007) asked respondents whether they had listened to four genres (opera/operetta, jazz, classical, and pop/rock) in the preceding four weeks. In the data used by Bryson (1996), by contrast, respondents were given 18 genres, with the instruction to indicate their preference or dislike for each on a five-point Likert scale. Between these two, the questionnaire used by Peterson and colleagues (Peterson & Kern, 1996; Peterson & Simkus, 1992; Peterson, 1992) instructed respondents to indicate whether or not they liked 10 genres. The consequences of this variety for the operationalization of music genre classifications should not be underestimated. Genres are important initial organizing tools for researchers, allowing them to classify people and draw links between these classifications and sociodemographic characteristics such as social class, age, and gender. Music genres shape boundaries within the music field and they "ultimately feed into sociology's conception of difference, class and inequality" (Beer & Taylor, 2013; p. 2). The boundaries created by classifying artists into separate genres are inevitably reflected in research that links culture with social divisions. Focusing on the issue of classification systems for music genres, and their possible drawbacks, therefore seems appropriate. We begin by listing the problems we see with music taste measurements based on a predefined list of genres.

First, cultural research that uses predetermined genre lists makes the assumption that genres are rigid and stable concepts (Beer & Taylor, 2013; Lena & Peterson, 2008). This is at odds with the prevailing conviction that music genres continually emerge, evolve, and disappear (Beer, 2013; Lamont & Molnár, 2002; Lena & Peterson, 2008). Music genres are lively concepts, and boundary drawing around genres happens continuously within the dynamics of the field (Bourdieu, 1984; Savage & Silva, 2013). The emergence of decentralized social media seems to have accelerated the dynamics even more. The field of music genres shows signs of 'declassification' and of becoming more "differentiated and characterized by a plethora of genres" (Beer, 2013; Dimaggio, 1991; van Venrooij, 2009, p. 317). A predefined list of genres is unable to deal with this vibrancy. It assumes that researchers can keep up with the unremitting dynamics of genre boundary drawing in their research context. In practice, it is almost impossible for an 'uncool' cultural researcher to capture emerging, evolving, and disappearing genre boundaries in a predetermined grid (Beer, 2009; Lamont, 2010). Dimaggio (1987) has already drawn attention to the fact that survey questions make fewer distinctions between cultural forms than users of culture do. In particular, broad genre definitions tend to overlook "sub-divisions into genres, periods, styles, authors etc." (Bourdieu, 1984, p. 16; Savage, 2006).

Second, there is no guarantee that a presented music genre list is interpreted universally. Respondents can have different understandings of what type of music fits in a particular genre (Beer & Taylor, 2013; Holt, 1998; Savage, 2006). For example, as stated by Beer, "an artist like Eminem might be pop for one person and hip-hop for another" (Beer & Taylor, 2013; p. 3). This relates to qualitative research that shows, for example, how respondents discriminate between 'light classical' and 'avant-garde' classical music. Bourdieu's own analysis on music taste even differentiated between two works by the same artist (Bourdieu, 1984, pp. 16–17; Savage, Bagnall, & Longhurst, 2005). Cultural research based on music genre preferences ignores all the interpretational variety within the music genres: a predetermined grid of genres leaves no room for 'fuzziness' in interpretation (Beer, 2013; Bottero & Crossley, 2011).

Finally, when asking about music preferences we do not know whether people have actually heard the music encompassed by the presented genres (Savage, 2006). Research has shown that people have stereotypes about music genres, over and above their preferences or dislikes for the intrinsic musical properties of these genres (Rentfrow & Gosling, 2007; Rentfrow, McDonald, & Oldmeadow, 2009; Van Steen & Lievens, 2011). The positive or negative feelings about music genres that people express can be due to stereotyping instead of a real taste preference. These connotations are socially structured as “musicians (. . .) can be located sociologically” (Sonnett, 2016; p. 41), so some scholars suggest that music genre preferences are actually ‘sociocultural identifications’ associated with these genres and not a real taste measurement (Bourdieu, 1984; Holt, 1997; Savage, 2006; p. 167).

2.2. Consequences

The problems associated with the use of predetermined music genre lists may have far-reaching consequences for research on the prevalence of the cultural omnivore. By using such a lists, researchers have no control over variety in interpretation or listening preferences versus stereotypes, and they risk missing important subgenres and styles within genre categories. This corresponds with research that emphasizes the importance of within-genre diversity. Atkinson (2011), for example, claimed the existence of a polarization between legitimate/artistic and popular/commercial *within* every music genre. This is perhaps most tangible for classical music, where even Bourdieu made a clear distinction between ‘easy listening’ and more esoteric or avant-garde forms (Bourdieu, 1984; DeNora, 2000). Following this insight, it is possible that it is not just a combination of music genres that identifies cultural omnivores, but a combination of specific aspects and even artists or works within and across music genres that serve as taste markers for omnivorousness (Holt, 1997). Consequently, it is possible that omnivorousness measurements based on music genre preferences overlook boundary crossing within genres. Alternatively, on the other hand, respondents who like different music genres may actually combine only the ‘legitimate’ or non-legitimate sections of these genres, where “legitimate” refers to taste from the ruling class, as Bourdieu (1984) puts it. Survey research based on predefined genre categories is not capable of distinguishing between these different types of preference patterns.

As a response to these issues, we follow Lamont’s call to find ways to study “classification systems comparatively and from the ground up” (Lamont, 2010, p. 132). We argue for the use of more specific music taste measurements, such as artist preferences, to measure music taste from the bottom up and we show how a relational approach to respondents and their music artist preferences offers new methodological opportunities to study the classification of music taste comparatively.

2.3. Dropping the label

First, we propose the use of preferences for specific groups, singers, artists, and composers instead of for specific music genres. We view artist preferences as a middle ground between specific musical works and genre categories. As argued in the previous paragraphs, music genres are too broad, while an open question for music works may be too specific to find any overlap and systematic links between respondents and their music taste. By asking respondents to consider specific artists in an open question, we avoid problems of interpretational variety and avoid measuring stereotypes and dispositions towards music genres instead of real listening patterns (Savage, 2006). Furthermore, by using an open question instead of an ad hoc genre list, we tackle problems of hidden dimensions and strong dynamics in music genre boundaries. Researchers will not have to produce a list of genres anymore, which eliminates the risk of using genre grids that are out of date or incomplete, and which do not capture all the dimensions in the music taste of respondents. This approach relates to Beer’s (2013) concept of ‘classificatory imagination’, in which genre boundaries are formed continuously through ‘negations in actions’. Rather than treating music genres as a stable set of classifications, cultural research should focus on how “boundaries are drawn and redrawn in a changing cultural context” (Beer, 2013; p. 157; Beer & Taylor, 2013). An open question on listening preferences for specific groups, singers, artists, and composers allows us to study music taste from the bottom up, within the context of everyday social interaction.

Next, we argue for adopting a relational view on respondents and their music artist preferences. We agree with other scholars that a focus on what is termed the duality between people and cultural products can offer new insights for cultural researchers (Breiger, 1974; Dimaggio, 2011). If we consider people and their artist preferences as a two-mode network, we can use network theory and methodology to analyze the interrelationships between different cultural items and their connection with people. As Dimaggio put it, in a two-mode network of artists and people, “genres consist of those sets of works which bear similar relations to the same sets of persons” (Dimaggio, 1987, p. 441, footnote 3). This means that if we construct a two-mode matrix with people on the first mode and artists on the second, we can identify clusters of music works that are strongly connected and are often associated together by a group of respondents (see also Mark, 2003). In other words, a first mode will reveal music genres ‘from the ground up’, based on artist preferences, and a second mode will reveal groups of respondents that have similar relationships to the clusters of artists in the first mode. These clusters of respondents are taste groups: each of them will have a distinct artist preference pattern, which allows us to detect cultural omnivores and univores based on self-reported artist preferences. Finally, the clusters of people can be linked to sociological indicators, thus allowing us to detect the social distinctions in the detected clusters of respondents.

In the following paragraphs, we apply our analytical strategy to the dataset. We use an Infinite Relational Model (IRM) to find clusters of artists and people, and compare our results with international findings on the cultural omnivore.

3. Data

We use data from the survey ‘Participation in Flanders 2009’ (Lievens & Waege, 2011), a research project from the policy research center ‘Culture, Youth and Sport’. Flanders, the Dutch speaking part of Belgium, has about 6 million inhabitants. In this survey, 3144 respondents between 14 and 85 years old, randomly selected from the National Register, were asked about their sociodemographic characteristics and their cultural behavior in a broad range of domains (arts, everyday culture, leisure activities, sport, and recreation). Each of these were measured in detail, providing a detailed picture of cultural participation in Flanders and giving insight into motives, expectations, thresholds for participation, and broader attitudes toward culture and society. The response rate in the sample was 68% of the eligible participants. The data is weighted by gender, age, and educational level in order to make it representative of the total population of Flanders aged 14–85. In addition to face-to-face interviews, data was gathered from family members using written, drop-off questionnaires. The latter data is not used here, as it provides insufficient information concerning our research questions. A comparison of this dataset with other international datasets on cultural taste and participation, which shows the unique qualities of the Flemish participation data, can be found in Kirchberg and Kuchar (2014).

This paper focuses on socio-demographic variables and on an experimental open question about the respondents' favorite artists. Half of the respondents in the sample (n = 1523) were randomly selected to answer the question: "Only for the genres you listened to in the past month, give about three names of groups, singers, artists, or composers you prefer to listen to. This question is only about what *you* prefer to listen to. There are no 'wrong' answers". This question was then followed by a list of 17 different music genres: baroque music, classical music, contemporary classical music, opera, operetta; soul or funk; rock, hard rock or heavy metal; dance, house, techno or drum and bass; world music; folk or country; popular Flemish music or Schlager music; jazz or blues; rhythm and blues, hip hop or rap; cabaret or chanson; brass band, and pop. Respondents could provide up to three names per genre or indicate "I did not listen to this genre". The list was used in order to provide some structure for the respondents, analogous to a semi-structured interview. It provided a framework for the respondents, as pre-survey tests revealed that an open question without this structure was perceived as very complex by respondents. The 17 presented genres were selected to be as broad and exhaustive as possible and was not meant to be a constraint for the respondents in any way. Therefore, for the subsequent analyses, we used aggregated data that disregards the abovementioned genre classifications. However, we do acknowledge that by pre-structuring the open question on artist preferences there is a possibility that the selection of the 17 genres might have influenced the artists mentioned by the respondents. Some artists may not fit into the presented genre list or, the other way around, some artists are more likely to be recalled because they are very closely related to a specific genre. However, previous research on the music preferences of the Flemish population already showed the relevance and importance of these 17 genres (Lievens & Waege, 2011; Vlegels & Lievens, 2013). That is why, combined with the pre-survey tests and taking into account the constraints of a CAPI-survey setting, we decided that the use of a genre framework for the open question on artist preferences was the best solution for this experimental question.

As sociodemographic explanatory variables, we include age, gender, education, socioeconomic status of the parents, and occupation. These five variables are known correlates of cultural taste. Age and gender are two widely-used control variables to predict cultural taste differences. Their effect is often at least as important as predictors of social class (Bennett et al., 2009, p. 2). Furthermore, in line with Bourdieu's (1984) well-known theory of social reproduction and Dimaggio's (1982) ideas on cultural mobility, we included measurements of personal educational capital, socioeconomic status of the parents, and occupational status. Univariate descriptive statistics of these categorical variables are presented in Table 1. To avoid issues with low cell frequencies in the multivariate analysis, we had to use rather broad categories for the age variable. However, we do know from other analysis on data from the same population that the age categories we defined are the most important divisions for music taste differences (see Lievens & Waege, 2011; Vlegels & Lievens, 2013). For the same reason, we combined students with unemployed and retired people in one category of the occupation variable. Students are already represented in the education variable, so it is redundant to make a separate category for them. Furthermore, because there are relatively few unemployed and retired people in the dataset, we had to combine them in the same category. We are therefore unable to detect possible different effects from unemployed versus retired people. However, previous research on the Flemish population does not uncover important distinctions between these different occupation types (Lievens & Waege, 2011; Vlegels & Lievens, 2013).

4. Method and results

4.1. Constructing a two-mode cultural network

First, we construct a two-mode matrix with respondents on the first mode and their favorite groups, singers, artists, or composers on the second mode. We end up with a 1523×1958 matrix, with respondents shown in the rows and the artists in the columns. But, only artists that are mentioned a few times by different respondents provide meaningful information for an IRM, as in other cluster analyses. This is because our method relies on the connections between respondents and artists. If an artist is mentioned only one or very few times there is not enough information available to get a robust allocation of this artist to a specific listening cluster. In that case, the IRM will choose the least worse solution, even though this is substantially meaningless. Therefore, we choose to reduce the original two-mode network before the analysis by selecting only artists with a minimum indegree of five. This minimum indegree tresshold avoids that we end up with meaningless 'rest clusters' in the results of our analysis. The need to define an indegree threshold for the IRM is inherent to any cluster analysis, and similar to defining a cutoff point in a hierarchical cluster analysis. We acknowledge that by using this minimum indegree of five, we risk missing clusters of more alternative music genres that are less popular in general, but still important as a listening

Table 1
Univariate descriptive statistics of Age, Gender, Education, Socioeconomic status of parents, and Occupation.

		Freq.	%
Age	−25	179	25.3
	25–34	112	15.8
	35–64 (ref.)	332	47.0
	65+	75	10.6
	missing	9	1.3
Gender	male	348	49.2
	female (ref.)	350	49.5
	missing	9	1.3
Education	student	152	21.5
	no/lower primary	121	17.1
	secondary (ref.)	140	19.8
	higher education	284	40.2
	missing	10	1.4
SES Parents	low	106	15.0
	medium (ref.)	234	33.1
	high	357	50.5
	missing	10	1.4
Occupation	student/unemployed/retired	306	43.3
	education/social work	97	13.7
	management/creative	100	14.1
	routine workers (ref.)	176	24.9
	missing	28	4.0

pattern. However, analyses on the two-mode network with a lower indegree threshold revealed similar results to those presented in this paper, but always included rest clusters in which we don't find any meaningful structure. Because of this threshold, the IRM results are based on a reduced matrix (707×350) that represents 17.88% of all the artists named in the open question, but since they are the most popular artists, they comprise 46.42% of all respondents. The indegree threshold hence predominantly influences the artist-mode, less the respondent mode. It is important to stress that the conclusions of our analysis are in essence still based on the information in the whole dataset, however, we decided to use a threshold before the analysis simply because this provides more comprehensible results. An IRM analysis on the non-reduced matrix produces the same artist and respondents clusters but adds a number of irrelevant and non-robust rest clusters because of artists with very low indegrees. This procedure is very similar to the cutoff point that is used to exclude clusters in a hierarchical cluster analysis. The density in the reduced two-mode network is 0.025, which means that 2.5% of all the potential ties between artists and respondents are actually present. In addition, the average indegree for artists is 11.78, indicating that an artist is mentioned by almost 12 respondents on average.

4.2. Infinite relational model

In the next step, we fit an IRM to the reduced two-mode matrix of respondents and artists (Kemp, Griffiths, & Tenenbaum, 2004; Kemp, Tenenbaum, Griffiths, Yamada, & Ueda, 2006). An IRM can be used to find an optimal cluster solution in bipartite graphs. IRMs simultaneously cluster the nodes in each domain. This starts by assigning each node of the two modes to a cluster according to the Chinese Restaurant Process (CRP). The CRP works in analogy to assigning customers to tables in a restaurant. It begins by assigning the first customer (node) to a table, and the next arriving customers (nodes) to existing tables with a probability proportional to how many customers are already sitting at the table and at a new Table Second, the probability for a link between two clusters is calculated. Finally, based on this information, the clustered network is formed. The advantages of an IRM are that is efficient enough to be used on relatively large networks. Traditional data-reduction techniques such as latent class analyses, Multiple Correspondence Analysis (MCA), or factor analyses are not applicable to a relatively large number of items. They are therefore not suitable for an analysis on an open question for artist preferences that typically generates a relatively large list of artists. The same is true for relational data-reduction techniques such as Relational Class Analysis (Goldberg, 2011) and two-mode block modelling, which are not able to deal with relatively large networks. Also, the inference of the IRM produces a posterior likelihood, so it is possible to select the most appropriate amount of clusters in the two modes without predefining the amount of clusters you expect in both modes of the relational dataset Finally, IRM is also fundamentally different from MCA as it clusters respondents and their artist preferences simultaneously without taking into account any other explanatory variable. These variables can be used in a next step, though, to look into the properties of the different clusters. And in this step, researchers are not confined to categorical variables in a low-dimensional Euclidean space, as is the case in an MCA analysis. More information on the method is

Table 2
Frequency of links between respondent clusters (horizontal) and artist clusters (vertical).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Classical voracious	32	25	65	35	0	53	1	0	33	0	14	23	4	27	0	2
2. Contemporary and international pop	0	0	1	0	0	0	181	9	0	49	14	0	0	0	182	65
3. Classical and classic pop	6	15	32	41	82	76	83	50	27	154	194	3	21	107	80	45
4. Classical and contemporary pop	40	63	103	107	50	185	4	63	103	42	353	9	49	349	0	0
5. Pop and rock across generations	0	3	0	0	108	0	22	109	0	187	466	0	56	337	65	6
6. Local and international pop	0	0	0	3	243	6	281	208	0	231	71	0	25	74	236	136

available in Kemp et al. (2004, 2006) and an example application in Larsen, Sapiezynski, Stopczynski, Morup, and Theodorsen (2013).

We select the model with the highest log probability and end up with 6 clusters of people and 16 clusters of artists. Table 2 shows the between-cluster links between the estimated clusters of respondents and artists, with clusters sorted by size in descending order. In Table 3, we dichotomize the between-cluster probability using standardized residuals. Only between-cluster links that have a standardized residual higher than two and thus have a significantly higher probability than expected by change ($p < 0.05$) are marked as black cells.

(1) Artist clusters

We start with an interpretation of the columns showing the artist clusters. The IRM identifies 16 different clusters of artists with a distinct relationship toward our respondents. The cluster analysis identifies as many artist clusters as needed to capture all the different listening patterns visible in the rows of Table 2. For each of the 16 artist clusters, sorted by size, Table 4 presents the number of artists included (n), valid percentage, average indegree and where possible, the five most central artists of each cluster.[1] These central artists are good representations of the content of each cluster. We use a closeness centrality measurement, as this expresses the average social distance from each actor (i.e. artist) to every other actor in the network. High closeness centrality actors tend to be important within their local network community (Freeman, 1978; Wasserman & Faust, 1994).

The first three clusters each contain only one classical music composer. These are, respectively, Mozart–with a very high indegree of 223 and therefore a very popular artist in our dataset–Puccini, and Verdi, two Italian composers. The fourth cluster contains only two artists, both of them are well-known Dutch singer-songwriters: Boudewijn de Groot and Bart Peeters. Next, the fifth cluster contains two classical composers: Handel and Strauss. Both are known for their operas and major concertos. In cluster 6, there are Milk Inc., Rihanna, and Beyoncé, three very popular, contemporary international artists in the pop and dance scene. The seventh cluster ($n = 3$) has a high mean indegree of 123 and contains very popular classical music composers: Bach, Beethoven, and Vivaldi. Cluster 8 is slightly larger ($n = 4$) and includes Metallica, Clouseau, AC/DC, and U2: four very popular rock bands that are still active and known for their stadium tours. Cluster 9 contains six somewhat less popular (average indegree 31.33) classical composers, including Chopin, Tchaikovsky, Schubert, Grieg, and Wagner. The artists in cluster 10 are commonly classified as pop, pop-rock, and Schlager music, mostly for an older generation. The five most central of them are Madonna, Coldplay, Michael Jackson, Marco Borsato, and Natalia. The artists in cluster 11 are contemporary international pop and rock acts, such as Eminen, Britney Spears, 50 Cent, Kings of Leon, and Tiësto. Cluster 12 contains classical composers such as Bizet, but also jazz composers and artists such as Billie Holiday. The average indegree of these composers and artists is low (9.57), indicating that they are not as popular as the other classical artists and perhaps more typical of a connoisseur. Cluster 13 contains rock and singer-songwriter artists, predominantly from

Table 3
Dichotomized between-cluster probability between respondent clusters (horizontal) and artist clusters (vertical).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	n
1. Classical voracious	■	■	■		■		■		■			■					31
2. Contemporary and international pop						■									■	■	74
3. Classical and classic pop							■			■							74
4. Classical and contemporary pop	■	■	■		■		■		■		■			■			165
5. Pop and rock across generations										■	■		■	■			177
6. Local and international pop				■		■		■		■					■	■	186
n	1	1	1	2	2	3	3	4	6	10	19	23	29	39	75	132	

[1] Table A.1 in the online Appendix shows the complete list of the artists in each cluster. Because this table was too extensive to include in the paper, we chose to present an abbreviated version with the five most central artists in each cluster (based on closeness centrality).

Table 4
The 16 artist clusters sorted by size (n), their valid percentage, average degree, and up to five most central artists based on closeness centrality.

#	n	valid%	average degree	#1	#2	#3	#4	#5
1	1	0.29%	223	Mozart				
2	1	0.29%	36	Puccini				
3	1	0.29%	91	Verdi				
4	2	0.57%	97.5	Boudewijn De Groot	Bart Peeters			
5	2	0.57%	60.5	Handel	Strauss			
6	3	0.86%	103.33	Milk Inc.	Rihanna	Beyoncé		
7	3	0.86%	123	Bach	Beethoven	Vivaldi		
8	4	1.14%	147.5	Metallica	Clouseau	AC/DC	U2	
9	6	1.71%	31.33	Chopin	Tchaikovsky	Schubert	Grieg	Wagner
10	10	2.86%	65.6	Madonna	Coldplay	Michael Jackson	Marco Borsato	Natalia
11	19	5.43%	36.42	Eminem	Britney Spears	50 Cent	Kings of Leon	Tiësto
12	23	6.57%	9.57	Bizet	Wim Mertens	Billie Holiday	Rachmaninov	Purcell
13	29	8.29%	40.62	Jacques Brel	Raymond vh Groenewoud	Will Tura	The Rolling Stones	Wannes Van de Velde
14	39	11.14%	20.62	Deus	Nirvana	Gorki	Bon Jovi	Tina Turner
15	75	21.43%	9.31	Jay-Z	The Killers	Stan Van Samang	Bob Sinclar	The Black Box Revelation
16	132	37.71%	10.22	Bob Dylan	James Brown	Axelle Red	Dolly Parton	Eric Clapton

an older generation, such as Jacques Brel and The Rolling Stones. The next cluster is dominated by rock bands and represented by Deus, Nirvana, Gorki, Bon Jovi, and Tina Turner. Cluster 15 contains artists such as Jay-Z, The Killers, Stan Van Samang, Bob Sinclar, and The Black Box Revelation. These are rock, pop, dance, and hip hop acts, mostly from recent generations. Finally, the last cluster is very large (37.71% of all the artists) and contains artists of all kinds of different music styles and generations. The puzzling interpretation of this cluster, combined with the low mean indegree of the artists, suggests that this is a 'rest cluster' of weakly connected artists. This kind of large rest cluster is the result of both the characteristics of the dataset we use and the method. Because we use an open question for artist names in a survey setting, this results in a large amount of artists that are mentioned only very few times. Combined with the fact that the IRM analysis finds clusters based on the links between artists and respondents, a rest cluster of weakly connected artists is almost inevitable. However, as mentioned before, we did use a threshold on the artist indegree to avoid ending up with meaningless rest clusters as much as possible. Still, it is impossible to know with our data whether this last rest cluster indicates that there is a group of respondents that are deliberately not following the cluster logic of other respondents, or whether this rest cluster is an artifact of a combination of the method with the data collection method. This question can potentially be resolved in future research that uses alternative big data sources, as we will discuss in the discussion section of this paper.

In general, we can conclude that these artist clusters, based on listening preferences, do not follow music genre boundaries. First, we see quite a lot of music genre boundary crossing within the clusters. For example, artist cluster 15 contains Jay-Z, The Killers, and Bob Sinclar. Three artists commonly known for, respectively, hip hop, rock, and house music. Similarly, in artist cluster 12, we find the classical composer Bizet as well as the jazz artist Billie Holiday. It is apparent if we analyze the objective relationships between artists, based on the music preferences of respondents, that artists are not necessarily clustered based on their music genre affiliation. In some cases, distinction between the different genres is not necessary to detect different listening patterns; hence the music genre boundary crossing within our artist clusters.

Second, the artist clusters show a great deal of diversity *within* music genres. For example, the IRM identifies no less than seven different clusters (1, 2, 3, 5, 7, 9, and 12) that contain composers who would commonly be classified as producing 'classical music'. This is a first indication for the existence of a differentiation *within* music genres. Music genres are too broad to serve as a taste marker, as boundaries are drawn between respondents based on differences in music preferences *within* music genres. This is most striking for classical music, but also true for other genres such as pop music (e.g. clusters 6 and 11) or rock music (e.g. clusters 8 and 14). The IRM identifies as many clusters as necessary to detect all the different listening patterns of our respondents, and is much more detailed than a survey based on broad music genre boundaries would be.

(2) Respondent clusters

The IRM identifies six respondent clusters, presented in the rows of Table 2. Each of these clusters illustrates a group of respondents that has a similar relationship to the vertical artist clusters. They are groups of people who have similar artist preference patterns. An interpretation of these respondent clusters allows us to identify different types of cultural omnivores and univores, based on artist preferences. We discuss the content of the clusters sorted by size in ascending order, as presented in Table 3.

The first respondent cluster combines artist clusters 1, 2, 3, 5, 7, 9, and 12. All of these contain classical music composers, the last also contains two jazz musicians. Summing up, respondents in the first cluster have a somewhat univore taste in terms of music genres, as they mainly like classical music composers. However, they are also quite voracious within the classical music genre, as they combine all sorts of different classical music. For example, they typically listen not only to Mozart, but also to as Wim Mertens, a contemporary classical artist. We label this first cluster as 'classical voracious'.

The respondents in the next cluster are linked to artist clusters 6, 15, and 16. Cluster 6 contains three contemporary international and very popular pop and dance music artists, and cluster 15 comprises rock, pop, dance, and hip hop artists, also from a recent generation. In addition, artist cluster 16 is the very large rest cluster, which contains all kinds of different music styles and generations. Summarized, respondents from the second cluster have a preference for popular, mostly contemporary music artists, and we define them as 'contemporary and international pop'. The third respondent cluster combines only two artist clusters: 7 and 10. Cluster 7 contains three of the most popular classical music artists: Bach, Beethoven, and Vivaldi. Cluster ten contains very popular artists in the pop, rock, and Schlager categories, mostly from an older generation. This third respondent cluster seems to encompass cultural omnivores, based on music genre crossing, as they combine classical music with pop and rock. However, on the other hand, they prefer the most popular artists in these genres, which might be an indication that they only combine a specific kind of artist across genres. We define this third cluster as 'classical and classic pop' enthusiasts.

The fourth cluster of respondents is similar to the first, except that it does not include artist cluster 12, containing connoisseur classical and jazz artists. The respondents in cluster four are also linked to artists from clusters 11 and 14. These clusters contain recent generation artists from rock, pop, and dance bands. Therefore, based on music genre boundary crossing, we can state that respondent cluster four contains cultural omnivores who combine classical music with contemporary rock, pop, and dance music. We term them 'classical and contemporary pop' omnivores.

Next, the fifth cluster of respondents is linked to artist clusters 10, 11, 13 and 14. Clusters 11 and 14, as in the previous respondent cluster, contain contemporary artists in the fields of rock, pop, and dance music. Artist cluster 10 contains pop artists, mostly from older generations, and cluster 14 includes rock bands from a different generation. Respondents in cluster five focus more on smaller bands and do not include any of the large 'stadium' pop and rock artists. Summarized, they predominantly listen to smaller rock and pop artists from different generations, we label them 'pop and rock across generations'.

Finally, the last respondent cluster, 'local and international pop' is linked to artist clusters 4, 6, 8, 10, 15, and 16. This implies that respondents in cluster six prefer Dutch singer-songwriters as well as a wide range of pop and rock artists, all internationally oriented.

Again, these respondent clusters do not follow traditional music genre boundaries. Combinations of artist clusters seem to be formed based on the generation, popularity, and internationality of the artists. Only one listening cluster–the first–combines all seven of the artist clusters that contain classical composers. All the other listening clusters combine different aspects of music genres. Some of them focus only on music from recent generations (e.g. cluster four), others predominantly like very popular artists in different genres (e.g. cluster three) or concentrate on international acts (e.g. cluster six). Differentiation between the different artist preference patterns is not based on traditional music genre boundaries, but on more subtle differences between multi-genre artist clusters. The results suggest that within-genre diversity is more important than that between genres. In the next paragraph, we explore the social distinction between the six different listening patterns detected.

4.3. Binomial logistic regressions on cluster membership

The above description of the six respondent clusters identified by the IRM is a presentation detailing which clusters of artists are preferred by groups of similar people. However, from a sociological point of view we need to explore how these different music preference patterns are related to the social background of the respondents. In this way, we can grasp the social distinction between the different listening clusters based on shared artist preferences. Accordingly, Table 5 reports the results of a series of logistic regressions on respondent cluster membership. We are interested in which particular social groups are under or overrepresented in each of the six listening clusters. To avoid calculation problems due to low cell frequencies in the logistic regressions with several independent variables, the results are based on bootstrapped standard errors (number of samples = 1000). Nevertheless, we deleted coefficients based on a cell frequency lower than five. A statistically significant odds ratio higher than one indicates that a specific category is more likely to be a member of a cluster, compared with the specified reference group. In contrast, a statistically significant odds ratio lower than one indicates that a category is more unlikely to be a member of a cluster, compared with the reference category. As discussed in the data section, we include known predictors of cultural taste, such as age, gender, education, socioeconomic status of parents, and occupation. The reference categories for these variables are respectively people between 35 and 64 years of age, female, only secondary education, average socioeconomic status, and routine workers. In the following paragraphs, we discuss briefly the most important determinants for each respondent cluster.

The first respondent cluster, grouping together people with a voracious preference for classical music, predominantly comprises older people (odds ratio for 65+ = 6.50). Other socio-demographic variables such as gender, parents' socioeconomic status, and occupation do not produce significant results. This first respondent cluster therefore seems to consist of an audience of older people, regardless of other variables.

For respondent cluster two, contemporary and international pop music, the picture is somewhat different. Here, we see that the cluster is predominantly associated with respondents younger than 34. The odds ratio for under 25 years is a very high 13.30 and for respondents between 25 and 34 it is 6.97. Furthermore, this is also reflected in the exceptionally high odds ratio for students: the odds for them being a member of this second cluster are about 12 times higher than for the reference

Table 5
Logistic regressions on cluster membership (sign. based on bootstrapped standard errors with number of samples = 1000).

		Classical voracious		Contemporary and international pop		Classical and classic pop		Classical and contemporary pop		Pop and rock across generations		Local and international pop	
		exp(b)	Sign.	exp(b)	Sign.	exp(b)	Sign.	exp(b)	Sign.	exp(b)	Sign.	exp(b)	Sign.
Age	−24	+	+	13.30	0.00	0.34	0.05	0.29	0.02	0.43	0.10	4.33	0.00
	25–34	0.33	0.13	6.97	0.00	1.45	0.24	0.21	0.00	0.81	0.41	2.42	0.00
	35–64 (ref.)												
	65+	6.50	0.00	+	+	+	+	1.26	0.49	0.50	0.04	0.10	0.02
Gender	male	1.28	0.56	0.57	0.08	0.49	0.00	1.10	0.63	1.18	0.36	1.21	0.33
	female (ref.)												
Education	student	+	+	12.46	0.01	5.15	0.04	0.23	0.02	0.38	0.11	2.45	0.09
	no/lower primary	0.33	0.07	2.84	0.10	0.62	0.36	0.81	0.54	0.67	0.14	2.77	0.00
	secondary (ref.)												
	higher education	1.57	0.35	0.73	0.63	1.09	0.81	1.65	0.05	0.66	0.08	0.84	0.58
SES Parents	low	0.88	0.84	1.17	0.81	0.92	0.87	1.06	0.85	1.20	0.49	0.95	0.87
	medium (ref.)												
	high	1.31	0.60	0.80	0.56	1.31	0.35	1.56	0.04	1.05	0.83	0.64	0.05
Occupation	student/unemployed/retired	7.85	0.25	0.22	0.07	0.42	0.07	5.06	0.00	1.02	0.94	0.25	0.00
	education/social work	2.10	0.22	1.32	0.70	1.61	0.24	2.37	0.02	0.82	0.51	0.54	0.08
	management/creative	3.22	0.15	0.84	0.73	1.11	0.80	2.73	0.00	0.55	0.05	0.95	0.88
	routine workers (ref.)												
Constant		0.01	0.00	0.02	0.00	0.16	0.00	0.12	0.00	0.64	0.10	0.34	0.00

+ = cell frequency < 5.

group. Again, this second cluster is strongly defined by age and the other independent variables produce no significant results.

Cluster three, containing classical and classic pop enthusiasts, seems to attract middle-aged, predominantly female respondents. We find a significant odds ratio of 0.34 for respondents younger than 25 compared with the reference category of 35–64 years old. Furthermore, the odds of females being part of this cluster are about twice that of males. The other independent variables again do not produce any significant results.

The fourth cluster of classical and contemporary pop omnivores includes few young people. We find an odds ratio of 0.29 for people younger than 25 and an odds ratio of 0.21 for respondents between 25 and 34. However, this cluster notably includes respondents with a higher education background. Their odds of being in this cluster are 1.65 times higher than the reference category of only secondary education. The socioeconomic status of the parents is also relevant. Respondents whose parents have a high socioeconomic status have odds of being in cluster four that are 1.56 times higher than the reference category. Furthermore, we find significant effects for occupation: respondents working in education/social work and management/creative jobs have significantly higher odds of being a member of this fourth cluster than the reference category of routine workers. The odds for students, retired people, and other unemployed people to be in cluster four are also about five times higher than for routine workers. Cluster four is therefore the first cluster showing positive effects of education, socioeconomic status of the parents, and occupation. It is the undoubtedly the most exclusive cluster of the six.

For cluster five, pop and rock across generations, we find that the odds of being a member of this cluster are about two times smaller for respondents older than 65 compared with the reference category of 35–64 years old. In addition, the odds for people working in a management or creative job are about two times smaller than for routine workers. This fifth cluster therefore seems mostly to comprise people younger than 65 who do not work in a management or creative job.

Finally, cluster six, local and international pop, is defined by age, education, socioeconomic status of the parents, and occupation. We find that people younger than 34 have significantly higher odds than the reference category of being in this cluster, while respondents older than 65 have significantly lower odds than middle-aged people. More specifically, for people younger than 25 we find an odds ratio of 4.33, for respondents between 25 and 34 this is 2.42, and for people older than 65 it is 0.10. For education, we find that the odds for people with no or only lower primary education being a member of cluster six are 2.77 times higher than the reference category of people with only secondary education. Further, for respondents whose parents have a high socioeconomic status we find a significant odds ratio of 0.64. Finally, the odds of being in cluster six are 1.56 times lower for students, retired, or other unemployed people than for the reference category of routine workers.

In summary, we find several significant effects of the independent variables in the logistic regressions on respondent cluster membership. Two are of serious interest. First, for all six clusters we find that age is an important factor to explain cluster membership, even after controlling for gender, education, parents' socioeconomic status, and occupation. All the music taste patterns are clearly defined by age. Some appeal to a young public ('contemporary and international pop' and 'local and international pop'), one is almost exclusively linked to people older than 65 ('classic voracious'), and others are more typical for middle-aged respondents as they are disliked by young people ('classical and classic pop' and 'classical and contemporary pop') or older respondents ('pop and rock across generations'). Age is thus one of the primary explanatory variables for our music taste pattern clusters.

Second, it is notable that only one of the six clusters, classical music and contemporary pop, attracts people with a higher education level, high socioeconomic status of the parents, and a high status occupation. This fourth cluster is clearly an omnivore cluster, where the respondents typically combine two different music genres: classical music and contemporary pop music. However, our analyses also identify several other omnivore clusters. The third respondent cluster, for example, with people combining classical music and classic pop. Cluster five, for people combining pop and rock music, could also be interpreted by some scholars as an omnivore cluster. Nevertheless, only one of these omnivore clusters, cluster four, attracts respondents from higher social strata.

4.4. Comparison with 'traditional approach'

Finally, in this last step, we compare the results of our method with a more 'traditional' approach on music taste classification. As argued in the introduction, there is no real consensus in the literature on how to operationalize music taste patterns. However, researchers typically use a similar workflow when they try to the classify music taste of their respondents into taste patterns. First of all, researchers ask their respondents to indicate their preferences for a list of music genres. Next, they reduce these music genres preferences to more broad listening categories and finally, they combine these broad categories to identify different types of univores and omnivores. We now adopt a similar workflow on our dataset so we can compare the result of this more 'traditional' approach to our new method presented above. A comparison of both methods can highlight the differences between the two methods and possibly confirm our findings and conclusions presented in the previous chapters.

In our questionnaire, we listed the same 17 music genres used to structure the question on artist preferences presented before. Respondents were asked how often they had listened to each of these genres during the month preceding the survey. Answers were on a five-item ordinal scale, ranging from 'not during the last month' (=1) to 'daily' (=5). Next, we reduced the 17 music genres to three different overall music taste categories: highbrow music, pop music and folk music. These three broad music taste patterns are repeatedly found in similar representative datasets of the Flemish population in Belgium (Lievens & Waege, 2011; Van Eijck & Lievens, 2008, Vlegels & Lievens, 2009). The highbrow music category includes baroque music, classical music, contemporary classical music, opera and operetta. The second category, pop music, contains dance, house, techno or drum 'n bass, r&b, hiphop or rap, pop music; rock music; hardrock or heavy metal music; soul or funk, world music; jazz or blues; folk or country; brass band; and cabaret or chanson. The last, folk music, comprises popular Flemish music or Schlager music. The standardized mean scores over these different genres in each of the three categories is then divided into five classifications: from a very low interest through an average interest to a very high interest, resulting in an ordinal variable with a range from 1 to 5. The reliability figures (Cronbach's Alpha) for the highbrow category is 0,75, for the pop music category this is 0,69. Since folk music contains only one genre label (cabaret or chanson), it is redundant to calculate the internal consistency. Next, we can construct eight different listening patterns: three different types of univores, four different combinations of omnivores and one category for non-listeners. We allocate every respondent to one of these seven categories if they have an above average interest for that specific listening pattern. Table 6 gives an overview of the results of this method.

A cross tabulation of this 'traditional' method with the results of the two-mode clustering then allows us to compare the outcomes of both methods (see Table 6). The frequencies and column percentages in Table 6 show how the respondents from the traditional top-down approach are distributed across the eight different listening patterns based on the two-mode clustering of artist preferences. In addition, we included age in this table as third layer, as this variable highlights the differences between the two methods we compare.

In general we can say that the listening clusters based on artist preferences do not correspondent with the clusters based on the more traditional method that combines genre preferences. The respondents in the traditional genre clusters are very much spread across the six different clusters we found based on a two-mode cluster analysis. Furthermore, the dispersion of the respondents in the traditional genre based listening patterns across the different listening patterns based on artist and respondent preferences seems to be structured by age differences between the respondents. This shows in the table as very uniform age distributions within the rows, and very different distributions within the columns.

For example, a large part of the highbrow univore category (55,56%) corresponds with the classical and contemporary pop cluster. The respondents in this cluster are typically between 35 and 64 years old. But another 23,33% of the highbrow univores overlap with the classical voracious cluster, where respondents are typically older than 65 years old. The two-mode cluster analysis based on the artist preferences of respondents thus differentiates different listening clusters within the classical music genre. Respondents with different age profiles listen to a distinct cluster of artists according to the two-mode cluster analysis, a difference that is impossible to make with an analysis solely based on genre preferences. A similar pattern shows for the other different listening clusters based on genre pReferences

The large group of pop univores is spread across five of the six listening patterns based on the two-mode cluster analysis. In general, pop music lovers are younger than average, but still we notice some differences between the different listening groups based on the two-mode cluster analysis. For example, 16,94% of the pop univores can be found in the 'contemporary and international pop' cluster which is a very young group of respondents typically younger than 24 years old. This contrasts with the 8,06% of pop univore respondents that are found in the 'classical and contemporary pop' listening cluster. Respondents in this cluster are typically between 35 and 64 years old. This shows that listening patterns are formed based on specific combinations of artists within a traditional 'pop' label, but also across the genre labels, hence the 'classical and contemporary pop' listening pattern. Also, this shows that the specific clusters of artists that are combined with 'pop' artists differ according to the age of the respondents.

The same is true for the next univore category: folk univores. These folk univores, labelled according to the traditional method, are also spread across five of the six listening patterns based on the two-mode cluster analysis. Again, listening patterns based on the two-mode cluster analysis show a very uniform age distribution, while there are clear differences within the univore folk category based on the traditional method.

This trend is also found in the different types of omnivore listening patterns based on the traditional method. Overall, this cross tabulation highlights the differences between our two-mode cluster analysis based on open question on artist preferences and a more traditional music preference measurement based on a measurement of genre preferences. The traditional method clusters respondents based on their preferences for a genre label, while the two-mode cluster analysis shows that real listening patterns are not based on genre labels, but on combining specific clusters of artists. These artists clusters are not genre specific, but they seem to be primarily dependent of the age of the respondents. This confirms our

Table 6
crosstabulation of 'traditional' method with two-mode cluster analysis.

		Highbrow	Popular	Folk	Highbrow-popular	Highbrow-folk	Popular-folk	Highbrow-popular-folk	Non listener
Classical voracious	Age −24	0	0	0	0	0	0	0	0
	25–34	1	0	0	0	0	0	0	0
	35–64	8	0	0	1	1	0	0	0
	65+	12	0	0	2	6	0	0	0
	Total	21	0	0	3	7	0	0	0
	Column%	23,33%	0,00%	0,00%	4,55%	14,00%	0,00%	0,00%	0,00%
Contemporary and international pop	Age −24	2	17	4	5	0	11	2	15
	25–34	0	3	2	0	0	0	0	5
	35–64	1	1	0	0	0	2	0	2
	65+	0	0	0	0	0	0	0	0
	Total	3	21	6	5	0	13	2	22
	Column%	3,33%	16,94%	7,06%	7,58%	0,00%	12,26%	3,70%	17,89%
Classical and classic pop	Age −24	2	2	2	2	0	3	0	4
	25–34	1	6	0	8	0	0	4	1
	35–64	3	6	1	6	3	8	5	6
	65+	0	0	0	0	0	0	0	0
	Total	6	14	3	16	3	11	9	11
	Column%	6,67%	11,29%	3,53%	24,24%	6,00%	10,38%	16,67%	8,94%
Classical and contemporary pop	Age −24	3	3	0	4	0	1	1	1
	25–34	4	1	1	1	0	0	1	2
	35–64	30	6	7	20	11	5	10	13
	65+	13	0	3	1	17	0	3	1
	Total	50	10	11	26	28	6	15	17
	Column%	55,56%	8,06%	12,94%	39,39%	56,00%	5,66%	27,78%	13,82%
Pop and rock across generations	Age −24	0	9	2	2	0	5	0	4
	25–34	2	13	5	0	0	4	0	6
	35–64	7	12	23	4	5	16	12	27
	65+	1	0	4	0	4	0	1	6
	Total	10	34	34	6	9	25	13	43
	Column%	11,11%	27,42%	40,00%	9,09%	18,00%	23,58%	24,07%	34,96%
Local and international pop	Age −24	0	21	12	5	1	17	7	10
	25–34	0	9	6	2	0	16	4	4
	35–64	0	15	12	3	2	18	4	16
	65+	0	0	1	0	0	0	0	0
	Total	0	45	31	10	3	51	15	30
	Column%	0,00%	36,29%	36,47%	15,15%	6,00%	48,11%	27,78%	24,39%

expectation that respondents in reality do not consume music structured around the pre-defined list of music genres that cultural researchers like to use. Their artist preferences are clustered according to other features like generation, popularity and internationality of the artists, almost irrespective of traditional music genres. The ability of our two-mode cluster analysis based on artist preferences to create clusters across and within genres therefore creates different listening patterns then a more 'traditional' approach based on genre pReferences

5. Discussion and conclusion

The aim of this paper is to present an alternative strategy to measure music preference patterns 'from the ground up', which tackles the problems associated with the use of predefined music genre lists: the constant dynamics of music genre boundaries, interpretational variety, and stereotypes versus real listening patterns. Although the use of a preset array of genres to measure music preferences has been questioned by several scholars in cultural sociology (e.g. Beer & Taylor, 2013; Beer, 2013; Savage, 2006; van Venrooij, 2009), we could not find any previous empirical study that overcomes the issues associated with the use of ad hoc music genre lists. We adopted a relational approach to the cultural preferences of respondents, conforming to the recent 'network turn' in cultural sociology (see e.g. Dimaggio, 2011; Lizardo, 2006, 2013; Pachucki & Breiger, 2010; Vlegels & Lievens, 2013). This allowed us to apply network analyses methodology and not be limited to the 'traditional' methods used to identify taste patterns in cultural sociology such as, for example, factor analyses, latent class analyses, or multiple correspondence analyses (MCA). We used an open question on the artist preferences of our respondents and a state-of-the-art clustering technique (IRM) on the two-mode network of artists and respondents to identify clusters of people who have similar relationships to the same sets of artists. In this way, we could identify music taste patterns 'from the ground up' and, in a last step, identify the social distinctions in these respondent clusters.

Thanks to our new approach to identifying music taste patterns, we can draw several interesting conclusions. The first is that the artist clusters we find do not follow traditional music genre boundaries. The artist clusters show substantial diversity between, and also within, traditionally used music genres such as rock, pop, classical, etc. The cluster analyses show that artists are not necessarily clustered based on music genre affiliations and that traditional genre boundaries are often too broad to serve as a taste marker. Our findings show that it is relevant to distinguish between different types of artist clusters within the traditional genre boundaries. This is in line with other theoretical and empirical research that suggests music preference clusters are much more fine-grained than the divisions commonly used by cultural researchers (Beer & Taylor, 2013; Dimaggio, 1987; Savage, 2006). In addition, it draws attention to the fact that research based on predetermined genre lists might miss important dimensions in music preference clusters.

With regard to the respondent clusters, we detect six distinct patterns of listening preference. The formation of these clusters seems to be based primarily on the generation, popularity, and internationality of the artists between, but also within, music genre boundaries. The fact that most of these listening clusters combine specific aspects of music genres is in line with research that advocates the importance of using a compositional approach on cultural omnivorousness, instead of a simple count measurement (see e.g. van Eijck & Lievens, 2008). Nevertheless, we find that different types of cultural omnivorousness are not necessarily defined by combining different music genres, but by combining specific aspects within *and* across music genres. Again, research that uses traditional dimension-reduction techniques on genre preferences–for example factor analyses or latent class analyses–would miss these particular types of cultural omnivores.

Next, when predicting respondent cluster membership, age is one of the primary explanatory variables. Our results suggest that some music consumption clusters are almost exclusively linked to specific age groups, independent of education, occupation or parents' socioeconomic status. This finding shows, that the importance of age for understanding music taste patterns should get more attention in future research, especially in research that uses artist preferences instead of genre measurements. Age groups are more than just control variables, they are important when explaining taste difference between status groups, but also within these status groups. The importance of age and generation was already acknowledged by Bourdieu (1984), who mentioned that an opposition between the young and the old is always present within status groups. This corresponds with more recent research, such as that by Savage (2006) and Savage and Gayo (2011) who found that age is probably the most important axis around which musical taste is fractured in the United Kingdom. "The [age] division cross cuts those of class and educational inequality" (Savage & Gayo, 2011, p. 353). We believe that an analysis on the level of the artist instead of music genre prevails the importance of age differences even more. Age divides in music taste are often to subtle to detect on the level of music genres, but are visible when looking into specific artist preferences. Our results suggest that new generations define new boundaries between and within different socio-economic status groups, and these boundaries are subtle, on the level of the artist. This corresponds with recent research that shows emerging generational differences in music taste (van Eijck & Knulst, 2005; Purhonen, Gronow, & Rahkonen, 2011). Two different mechanisms seem to be at play here. First of all, nostalgia, as defined by Holbrook (1993), can explain why young people sometimes prefer older generation artists. While, on the other hand, new generations want to distinct themselves from the older generations (Prieur & Savage, 2013).

Finally, although we find several different omnivore clusters, only one of these attracts respondents from higher social strata. Furthermore, we do not find a pure univore music taste cluster. Even the first respondent cluster, classical voracious, is not exclusively linked to classical music, as we also find some jazz artists in this cluster. All the other respondent clusters clearly combine artists from different music genres. This finding again corresponds with research that emphasizes the importance of distinguishing between different types of omnivores. It also parallels research that advocates the use of fine-grained measurements of music taste that take into account all the relevant subdivisions between and within genres, periods, styles, and composers (e.g. Beer, 2009; Dimaggio, 1987; Savage, 2006). Moreover, it suggests that the social distinction of cultural omnivorousness is not just a matter of people combining different music genres, but about combining specific artists between and within traditional music genre boundaries.

This overview of the most important empirical findings from our research implicitly illustrates the principle implications of this paper for previous and future research. We would like to suggest that future research on music taste patterns should consider the consequences of using predefined genre lists. Our analyses show that the ever-changing boundaries around music genres require more dynamic research practices that consider the 'battleground' around musical fields and use 'classificatory imagination' instead of rigid classification systems (Beer, 2013; Savage & Silva, 2013).

Our analyses clearly show that the artist preferences of respondents do not follow music genre boundaries. Consequently, cultural research that uses music genres to construct taste patterns might be biased. Sociological differences that are found between different (combinations of) music genres could actually be the result of the classification of music into predetermined genres by a researcher. Volume and even compositional measurements of omnivorousness are therefore possibly artifacts of the 'classification culture' among researchers. Cultural omnivore measurements that use music genre preferences can overlook important genres and subdivisions within these genres. Therefore, they can miss cultural omnivores who combine specific aspects within and across traditional music genres. Our ground-up approach reveals the actual boundaries between the music preferences of respondents, including all the important subdivisions overlooked by top-down classification systems and without issues of interpretational variety. Furthermore, our approach is independent of the context of analyses. A predetermined genre list has to be tailored to the specific requirements of a survey. Researchers have to construct a suitable list for their specific sample. A survey among high school students, for example, requires a different genre list to that for a population survey on music taste. By contrast, in our bottom-up approach, boundaries between artists and respondents simply emerge from the data and are independent of the researcher's 'coolness' (Beer, 2009).

An important issue of this paper that can be addressed in future research is the fact that the results of an IRM cluster analysis becomes more robust as more data is available. For this paper, we were limited to the use of a survey questionnaire in a CAPI research setting. The benefit of this kind of methodological setting is that we can use a representative sample of the Flemish population. But, the relatively limited sample size also meant that we had to deal with artists that are mentioned only one or very few times, which lead us to use a indegree threshold. And, the use of a genre-framework for the questionnaire was necessary because pre-tests showed the importance of providing some structure for the respondents in the survey. Future research can overcome these problems by using data from other sources. Big data from online music providers, for example, can be used to measure music consumption in real life, and can offer even better bottom-up information on music taste patterns. The IRM cluster analysis would benefit from the amount of information you get out of these big datasets and the indegree threshold limitation will not be necessary anymore.

Finally, we hope that our paper illustrates how a network approach on the cultural taste of respondents can offer new opportunities for sociologists. Our two-mode cluster analyses on respondents and artist preferences is only one example of how cultural sociology and sociology in general can benefit from existing knowledge and new developments in social network analyses. We hope to see new applications of this 'network turn' in future research of cultural sociology.

Acknowledgments

The authors would like to thank Pieter De Pauw for his rigorous data cleaning and Sam Werquin for his generous help with the MATLAB coding.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.poetic.2016.08.004.

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