［招待論文：研究論文］

Musical Diversity in India

A Preliminary Computational Study Using Cantometrics

インドにおける音楽多様性

カントメトリクスを用いた計算的予備研究

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Abstract: The degree of musical diversity within and between societies is a topic of long-standing debate with theoretical implications for cross-cultural musical comparison. Standardized cross-cultural data on musical variation from Alan Lomax's Cantometrics Project newly made available via the Global Jukebox allows us to attempt to quantify this variation. Here we perform a case study of traditional Indian vocal music using the 37 Cantometric features for 207 traditional songs from 32 Indian societies. Principal Component Analysis identifies complexity of vocal style as the primary factor shaping musical variation in India, consistent with Lomax's previous analyses of global variation. We find only very minor musical differences on average between speakers of different language families (Indo-European, Dravidian, and Austro-Asiatic), but greater variation between societies within language families. Additionally, we demonstrate how quantitative analysis can be strengthened by observations from musicians with direct experience of local traditions and applied to local/regional musicological questions.

社会内、また社会間において、どれほどの音楽的多様性が存在するのか。これに関しては複数の文化に及ぶ音楽比較への論理的な考察と共に、長年議論されてきた。Alan Lomax のカントメトリクス研究によって標準化された、多文化にわたる音楽的バリエーションのデータは Global Jukebox により新たに利用可能になり、それによりこのバリエーションを定量的に分析することが可能になった。本研究ではカントメトリクスの 37 の特徴に基づき、インドの伝統的な歌に対するケーススタディを行った。分析対象はインドの 32 地域から選んだ伝統音楽 207 曲である。主成分分析によって求められた、インド音楽のバリエーションを形成する主な要素が、Lomax が世界中の音楽に対する先行分析で求めた結果と一致した。このことから、インドに存在する歌唱法の複雑性が示される。異なる語族の話者(インドヨーロッパ、ドラヴィダ、南アジア語族)の間には、ごく小さな音楽的差異しか見られなかったものの、同じ語族内の複数社会の音楽を比較した際には、より大きなバリエーションが見られたのだ。また、地域的な伝統を直接経験した音楽家と共同研究をすることによって、定量分析はより強固なものになり、さらに地域的な音楽学上の問いに対しても適用可能であることが示された。

Keywords: cross-cultural, diversity, music, India, Cantometrics
異文化、多様性、音楽、インド、カントメトリクス

1 Introduction

1.1 Quantifying cross-cultural diversity

The question of how to compare and quantify differences within and between societies is a challenge in cross-cultural research (Bell et al., 2009; Jacoby et al., 2020; Ross et al., 2013; Rzeszutek et al., 2012). In linguistics, for example, analyses of the evolution of Indo-European languages use one set of vocabulary to represent English, one to represent French, etc., and reconstruct the evolutionary history of these languages by quantifying and modeling the similarities and differences in these sets of vocabulary (Bouckaert et al., 2012). While this approach yields findings regarding variation between languages, it circumvents internal variation within languages (e.g., dialects). In contrast, analyses of variation among dialects within a single language can uncover important patterns, but these are then difficult to generalize and compare with other languages (Labov, 1994-2010). Simultaneously accounting for variation within and between languages is a major challenge and calls for careful choice of units of analysis and the variables used, and accounting for the specific variables implicated in variance.

This challenge may apply as much or more to other domains such as music, where internal variation can be substantial enough that, in many cases, a single example may not be representative of a society for the purpose of cross-cultural analysis. Alan Lomax's Cantometrics Project (Lomax, 1968, 1980; Savage, 2018; Wood, 2018) was a sweeping attempt to account for global musical variation and evolution using quantitative methods to compare music cross-culturally across a number of variables. It produced a dataset of approximately 6,000 songs that contained multiple songs from most societies. A criticism of the study was that too few examples were used to represent and account for internal variation within a society (cf. Savage, 2018; Wood, 2018). Lomax and his collaborator, Victor Grauer, maintained that in most societies one main musical style emerges, regardless of genre. One of the approaches used in Cantometrics was to derive "modal profiles" representing the most common musical characteristics for each society and compare these modal profiles cross-culturally. This treatment has been contested by some (cf. discussion and references in Savage, 2018), but its validity has yet to be comprehensively tested on a global scale.

Although the issue of how to quantitatively compare societies while accounting for internal diversity is complex, new statistical methods such as cluster analysis and the Analysis of Molecular Variance (AMOVA; Excoffier et al., 1992; Rzeszutek et al., 2012) allow us to test such assumptions and simultaneously quantify variation within and between societies. A study of 259 structural aspects of traditional group songs from twelve indigenous populations in Taiwan and the Philippines showed much greater variation within populations than between populations (98% vs. 2%, respectively; Rzeszutek et al., 2012), paralleling recent findings in genetics and in other domains of culture (Handley & Mathew, 2020). A recent study of global variation in musical behaviors, as recorded in ethnographic texts, also argued that music varied more within than between societies (approximately 75% vs. 15%, respectively; Mehr et al., 2019). Importantly, however, neither of these studies included data on singing style (e.g., vocal tension, vocal blend), which Lomax had argued was the aspect of music that varied least within societies and varied most between societies. Quantification of within vs. between society variation was not previously applied to Cantometric data on singing style because the data was not ready for public release until now.

The recent digitization and public release of Lomax's Cantometric data on the Global Jukebox (Wood et al., In prep.) and D-PLACE (Kirby et al., 2016) allows us to reanalyze Cantometric data to answer these questions about the structure of cross-cultural musical diversity. The Global Jukebox dataset includes standardized Cantometric classifications originally based on 37 musical features (Table S1; see Lomax & Grauer 1968 for full details) for approximately 6,000 traditional songs from approximately 1,000 societies (Fig. 1), in addition to various other cross-cultural expressive arts datasets and educational tools. Although the system was not designed to work at that level of analysis without weighting and considerable refinement, some critics argued that the validity of Cantometrics would depend on its ability to provide meaningful results at a local or regional scale (e.g., Feld, 1984). The goal of this paper is to attempt such a local/regional analysis focusing on the question of diversity within and between societies in India.

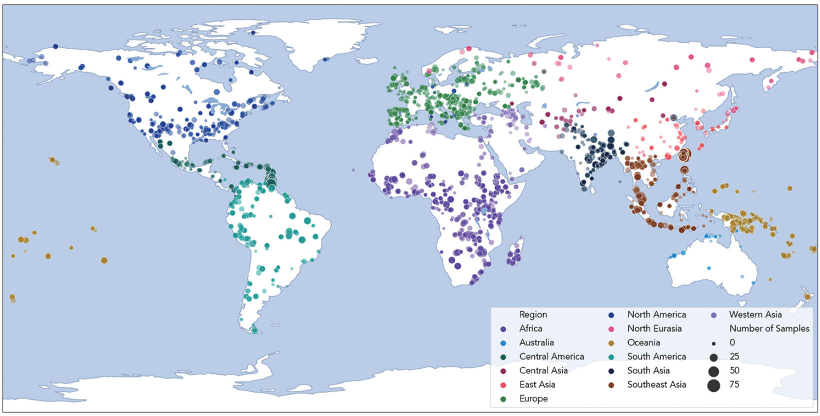

Figure 1 **A map of the current Global Jukebox sample of recordings of traditional songs that have been coded using Cantometrics. (from Wood et al., In prep.)**

1.2 Case study: Northern vs. Southern music in India

We chose India as the focus of our study because it allows us to explore multiple layers of diversity within the scope of a single country. India has both one of the largest populations in the world and one of the highest levels of cultural diversity, containing approximately 1/6th of the world's population and ~1/15th of its languages (Hammarström et al., 2020). It also has a long tradition of scholarly study ranging from pre-colonial treatises by Indian theorists to recent applications of state-of-the-art music information retrieval (MIR) technologies (Jairazbhoy, 1995; Rowell, 2015; Serra, 2017; Vidwans et al., 2019), and is an important emerging market for the music industry. Finally, our first author (HD) was born and raised in India with roots in both the north and the south (New Delhi and Chennai, respectively), allowing us to incorporate personal experience of living in India and playing Indian music as we interpret our results.

Music pervades all important aspects of Indian society, be they devotional, festive, or social on a smaller scale. Indian classical music is tied to tradition, folklore and history, and is intrinsically linked with Indian identity. A wide variety of musical styles make up what is known as Indian music. Although *Raga* and *Taal* (roughly analogous to scale and meter in Western music) characterize classical music theory, Western concepts of polyphony and harmony are essentially absent. Broadly speaking, one can consider the two categories of Hindustani (North Indian) and Carnatic (South Indian) as being the major styles that define Indian classical music (Wade, 1979; Binathi, 2012).

These Northern and Southern classical traditions are only one layer of musical style that coexists with and interacts with other styles such as popular and indigenous folk traditions, which may be shaped by other influences such as social layering, tribal influences, language, and global trade connections of great antiquity. The degree to which the northern vs. southern distinction is relevant beyond the classical traditions has not been previously tested systematically. Such an analysis could shed light on hitherto unexplored aspects of regional variation within India.

Linguistically, India is extremely diverse. Most Indian languages belong to two broad language families, Indo-European and Dravidian. About 73% of the population speak languages in the Indo-Aryan branch of Indo-European, while 24% speak Dravidian languages (Central Intelligence Agency, 2020; Meenakshi, 1995). There are a total of 450 tribal communities that speak 750 languages from the Austro-Asiatic, Dravidian or Tibeto-Burman (Singh, 1992; Kosambi, 1965) families, comprising roughly 3% of India's population.

Linguistic groupings are often used as a proxy for cultural groupings, but in many cases language and culture are not homologous. For example, a study of the Kol tribal populations suggests that in India, certain groups that have a different genetic ancestry share a common language as a result of sociocultural pressures to conform (Srivastava et al., 2020). Basu et al. (2003) suggest that the caste system blurred distinctions in local languages and forced several groups to adopt languages that favored upward mobility. Centuries of mixing, colonialism and migration have made these distinctions more and more interconnected. A long-standing debate on whether Austro-Asiatic or the Dravidian-speaking tribal groups were the original inhabitants of India (Thapar, 2003) has yielded plausible evidence suggesting Austro-Asiatic families predate the Dravidian settlement, and that Dravidians were pushed further south in order to avoid colonization (Basu, et al., 2003). Distinctions are not without classist undertones; upper caste Indians are largely closer to Central Asian populations. Religion favored the marriage of only certain communities of Indians from specific castes, resulting in a phenomenon where Indo-Europeans and Dravidians became major contributors to Indian culture and society.

Since cultural relationships cannot be completely predicted by language, music may offer an alternative to complement linguistics for predicting human population history (Lomax, 1980; Brown et al, 2014; Matsumae et al., 2019). Brown et al. (2014) found significant correlations between musical and genetic diversity among indigenous Taiwanese populations, suggesting that music and genes may have been co-evolving for quite some time. Meanwhile, similar studies comparing music, languages, and genes for a different group of northeast Asian populations found that grammar rather than language family classifications was a stronger predictor of population history than music (Matsumae et al., 2019). Overall, it appears that language, music, and cultural history vary somewhat independently (Feld & Fox, 1994; Pamjav et al., 2012; Brown et al., 2014; Matsumae et al., 2019), suggesting that care should be taken constructing analyses of music and its relationships with social groups and linguistic and cultural history.

Our goal is to look at the within vs. between culture variation in Indian music in order to get a broader understanding of Indian musical diversity and cultural history. Because language is often used as a proxy for cultural relationships, we will focus on a comparison between Indo-Aryan-speaking societies from northern India vs. Dravidian-speaking societies from southern India, excluding groups officially designated as “tribal”. But because language and official designations are imperfect cultural proxies, we will also include an analysis including all societies in India with Cantometric data (i.e., including the Portuguese-speaking Goa people, “tribal”, and/or Austro-Asiatic-speaking societies) to explore the extent to which musical patterns map onto linguistic ones (see map in Fig. 2 for details on the societies included, their language classifications, and musical sample sizes).

We will use the Cantometrics dataset to explore diversity within and between north and south Indian music based on 37 Cantometrics features (cf. Table S1 for a full list of features). Section 2 of the paper will look at a Principal Component Analysis (PCA) to visualize a representation of the dataset. We then perform an Analysis of Molecular Variance (AMOVA) to look at the degree of variance within and between societies. In section 3 we discuss our results and conclude with limitations and future directions for this research.

2 Methods

2.1 Musical sample

The standardized Cantometric classification data in the Global Jukebox allows us to quantitatively explore both similarities and differences in the repertoires of Northern and Southern India. The Cantometrics dataset contains standardized classifications for 37 musical features for 207 recordings from 33 societies throughout

India, including both classical (Hindustani and Carnatic) and folk traditions. While a majority of these recordings are classified as tribal (150 songs), we focus our analysis on the 57 recordings classified as 'non-tribal' (Ishtiaq, 1999; Central Intelligence Agency, 2020; Meenakshi, 1995). Of these, we focus on societies speaking Indo-

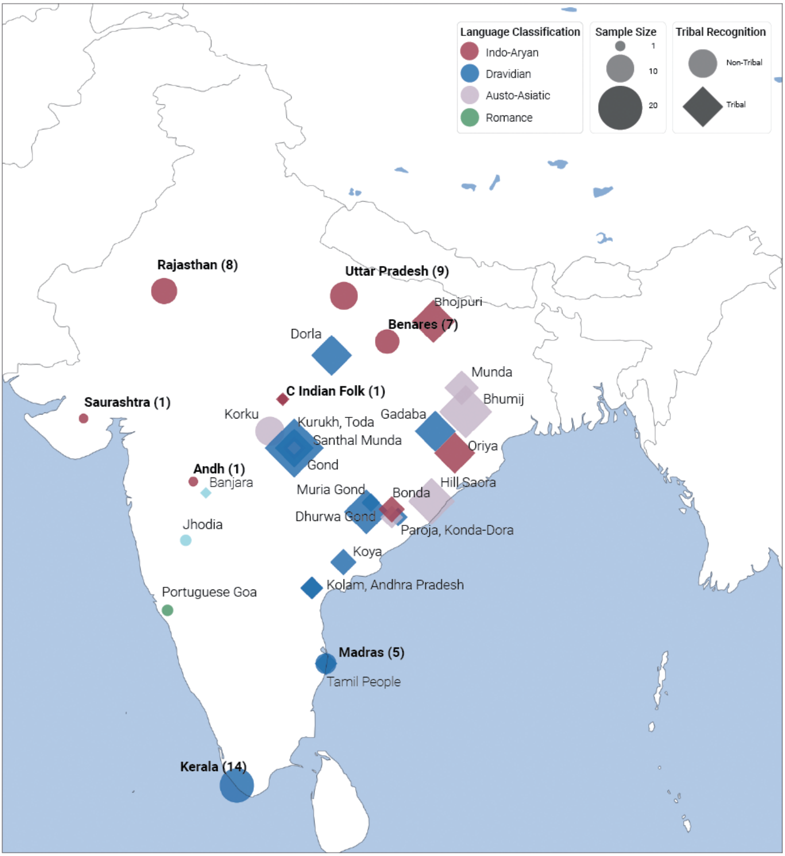

Figure 2 **A map of the Cantometric sample in India. Circle size indicates the number of songs, with 208 songs from 32 Indian societies, with a total of 101 songs from Dravidian-speaking cultures, 55 from Indo-Aryan-speaking cultures, 51 from Austro-Asiatic-speaking cultures, and 1 from Portuguese-speaking Goa (Portuguese belongs to the Romance branch of the Indo-European languages and is distantly related to the Indo-Aryan branch). Because the Goan sample was so small and its history so different from the rest of the sample, it was not included in the analyses.**

Aryan or Dravidian languages, with 28 and 19 recordings respectively. We omit from this subset the 10 recordings that are from Austro-Asiatic languages, as they trace an entirely different cultural lineage and comprise less than 3% of the total population (Honokla et al., 2018).

2.2 Principal Component Analysis (PCA)

To analyze and visualize musical diversity within the Indian sample of Cantometric data, we performed a Principal Component Analysis (PCA; Fig. 3). PCA condenses multidimensional data into a lower dimensional space by maximizing variance in each component (Wold et al., 1987), and is commonly used for multivariate analysis of cultural data, including music (Turchin et al., 2018; Mehr et al., 2019). We find that both the first and second principal components (PCs) each

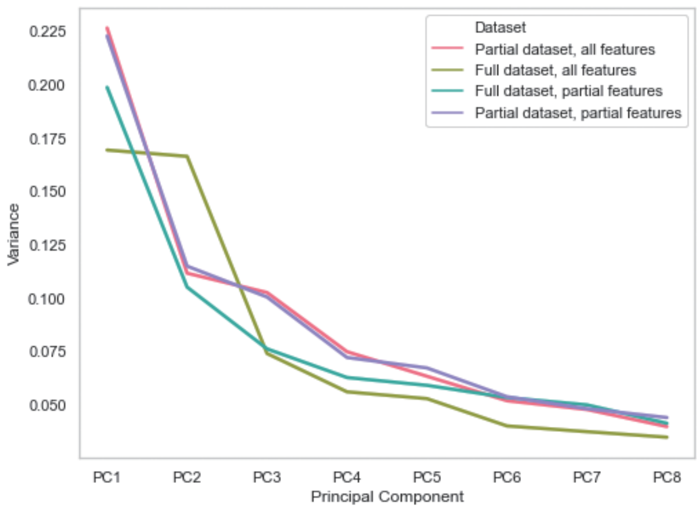

Figure 3　Scree plots of the various Principal Component Analyses (PCA) we conducted on our dataset. The *full dataset* consists of all 207 recordings (excluding Portuguese Goa), and *all features* means the PCA was calculated with all 37 Cantometrics features. A *partial dataset* denotes 47 (Indo-Aryan & Dravidian non-tribal) recordings, and *partial features* is PCA calculated with 26 features (excluding 11 quasi-redundant features). From these figures we can see the proportion of variance explained by eight principal components for all four PCs. See Table 1 for the variable loadings.

explain ~17% of variance in the 37 features. After this the proportion of variance explained suddenly drops to below 8% (see Fig. 3 for the proportion of variance explained by other dimensions). Upon re-conducting our analysis to include only Indo-Aryan & Dravidian non-tribal cultures, we find that the first PC explains ~23% of the variance and the second PC explains ~11%.

Importantly, the songs do not display any language-family or region based clustering. Instead, Indo-Aryan, Dravidian and Austro-Asiatic songs are dispersed widely across the two-dimensional space of the PCA (Fig. 4), suggesting that language family distinctions do not correlate with musical diversity within India.

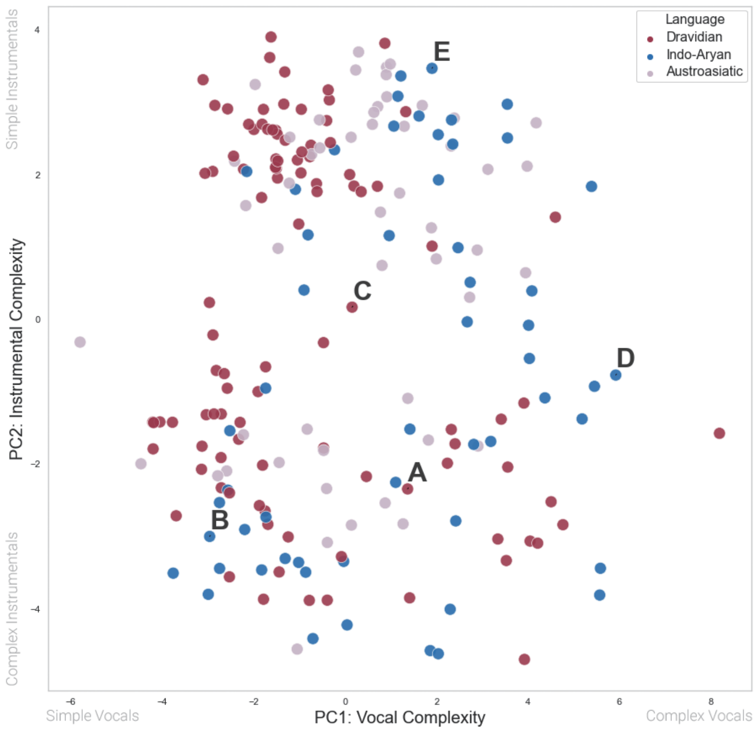

Figure 4 Full PCA plot of all 207 tracks measured across 37 features. We interpret the first two principal components as vocal complexity and instrumental complexity respectively. A, B, C, D and E are selected tracks discussed in greater detail in Fig 6.

We interpret Dimension 1 as being best described as capturing "vocal complexity". This is because dimension 1 is most strongly correlated with a collection of features spanning the diverse categories of musical organization (rhythmic coordination of the vocal group, tonal blend of the vocal group), vocal texture (musical organization of the vocal part, and tremolo), social organization (social organization of the vocal group), and articulation (repetition of text; see Table 1 for PC variable loadings). These all tend to covary such that solo singing tends to have more complex ornamentation and structure (appearing toward the right-hand side of Fig. 4), while group singing tends to be more repetitive and less ornamented (left-hand side of Fig. 4), consistent with correlations among features previously identified by Lomax (1980). We will use the term "vocal complexity" to describe PC1.

In contrast, PC2 does not correspond to a diverse set of categories; instead all of the features with the highest loadings are instrumental features (rhythmic relationship within the orchestra, rhythmic coordination of the orchestra, musical organization of the orchestra, social organization of the orchestra, and tonal blend of the orchestra). Songs appearing closer to the bottom of Fig. 4 tend to have larger, more coordinated instrumental accompaniment, while those closer to the top tend to be unaccompanied songs. We will use the term "instrumental complexity" to describe PC2.

The full sample analyzed in Fig. 4 is not entirely representative of Indian music demographically. The 2:5 ratio of non-tribal vs tribal recordings and the large number of Austro-Asiatic tracks in our sample are not proportional to actual population statistics in India, but the sample does capture an unusually diverse and complex set of cultural and historical relationships (Central Intelligence Agency, 2020). To investigate the impact of this sample, we redid the analysis on a smaller sub-sample of the Indian recordings after excluding tribal and Austro-Asiatic-speaking societies to focus more on the historical distinction between Indo-Aryan speaking societies in north India and Dravidian-speaking societies in south India.

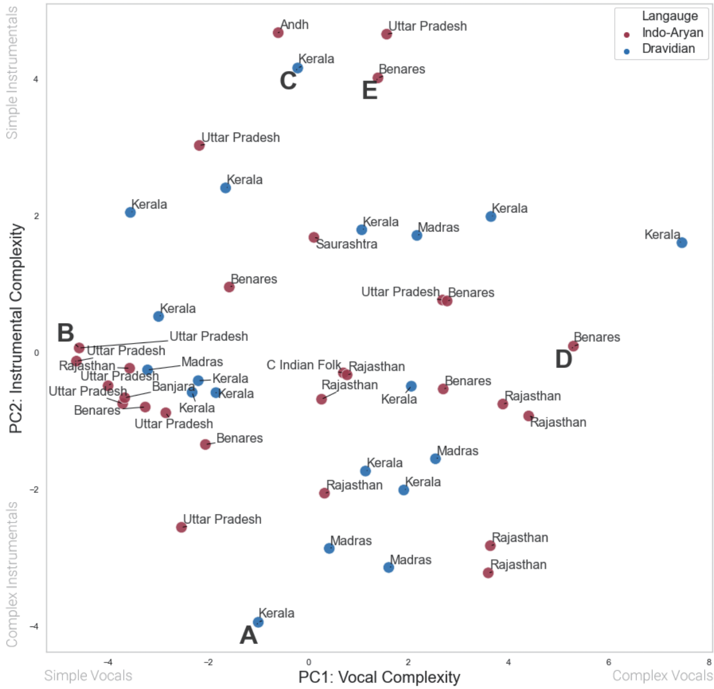

Figure 5 **The first two components from a PCA of the subset of 47 Indian songs from non-tribal Indo-Aryan and Dravidian-speaking populations in the Cantometrics sample. Individual points are shaded by language (Indo-Aryan vs. Dravidian) and labeled by society. Refer to Fig. 6 for a detailed description of each of the selected tracks A, B, C D, and E.**

Fig. 5 shows a revised PCA on a subset of the full sample. Here we exclude Austro-Asiatic and tribal societies. The 47-song sample also fits into similar principal components. PC1 corresponds with musical organization, ornament and social organization variables (rhythmic coordination of the vocal group, repetition of text, tremolo, and social organization of the vocal group). PC2 corresponds to the orchestral features: the musical organization of the orchestra, overall rhythm of the orchestra and social organization of the orchestra (Table 1).

Cantometric codings for five selected recordings from the dataset exemplify variation in style and form in this sample (Fig. 6). Example A, a devotional song from

Table 1　Variable loadings for the PCA plot shown in Fig. 4 (Full PC1& Full PC2) and Fig.5 (Subset PC1& Subset PC2).

Line	Title	Subset PC1	Subset PC2	Full PC1	Full PC2
1	THE SOCIAL ORGANIZATION OF THE VOCAL GROUP	-0.24	0.1	-0.24	0.14
2	RELATIONSHIP OF ORCHESTRA TO VOCAL PARTS	-0.02	-0.22	0.07	0.25
3	SOCIAL ORGANIZATION OF THE ORCHESTRA	-0.2	-0.3	-0.07	0.34
4	MUSICAL ORGANIZATION OF THE VOCAL PART	-0.23	0.16	-0.26	0.02
5	TONAL BLEND OF THE VOCAL GROUP	-0.23	0.16	-0.3	0.07
6	RHYTHMIC COORDINATION OF THE VOCAL GROUP	-0.27	0.11	-0.31	0.11
7	MUSICAL ORGANIZATION OF THE ORCHESTRA	-0.14	-0.38	0.0	0.36
8	TONAL BLEND OF THE ORCHESTRA	-0.11	-0.2	-0.08	0.32
9	RHYTHMIC COORDINATION OF THE ORCHESTRA	-0.19	-0.28	-0.09	0.34
10	REPETITION OF TEXT	-0.24	-0.09	-0.27	-0.02
11	OVERALL RHYTHM: VOCAL	0.15	-0.01	0.1	-0.13
12	RHYTHMIC RELATIONSHIP WITHIN THE VOCAL GROUP	-0.21	0.1	-0.24	0.06
13	OVERALL RHYTHM: ORCHESTRA	0.05	-0.33	0.09	0.29
14	RHYTHMIC RELATIONSHIP WITHIN THE ORCHESTRA	-0.22	-0.3	-0.09	0.34
15	MELODIC SHAPE	-0.09	-0.05	-0.06	-0.06
16	MELODIC FORM	-0.19	0.08	-0.23	-0.14
17	PHRASE LENGTH	-0.15	-0.02	-0.08	-0.09
18	NUMBER OF PHRASES	-0.18	0.02	-0.21	-0.12
19	POSITION OF FINAL TONE	0.11	-0.06	0.06	-0.03
20	MELODIC RANGE	0.06	-0.14	0.06	0.02
21	INTERVAL SIZE	-0.16	0.19	-0.21	-0.09
22	POLYPHONIC TYPE	-0.08	0.17	-0.14	-0.03
23	EMBELLISHMENT	-0.15	0.23	-0.23	-0.14
24	TEMPO	-0.16	-0.04	-0.14	0.03
25	VOLUME	-0.08	-0.27	-0.09	0.14
26	RUBATO: VOCAL	-0.23	0.01	-0.22	0.07
27	RUBATO: ORCHESTRA	-0.17	-0.04	-0.05	0.0
28	GLISSANDO	-0.2	0.05	-0.11	-0.03
29	MELISMA	-0.13	0.15	-0.16	-0.08
30	TREMOLO	-0.24	-0.09	-0.27	-0.01
31	GLOTTAL	-0.15	0.17	-0.12	-0.11
32	VOCAL PITCH (REGISTER)	-0.1	0.02	-0.06	-0.1
33	VOCAL WIDTH	-0.11	0.08	-0.12	-0.2
34	NASALITY	-0.09	0.05	-0.16	-0.1
35	RASP	-0.02	0.03	-0.06	-0.09
36	ACCENT	-0.1	0.02	0.04	-0.1
37	ENUNCIATION	-0.13	-0.1	-0.16	-0.08

Kerala, is a raga praising Hindu deities. The track relies mostly on the *tanpura* as a backdrop for the undulating male vocals in the *alaap* section. After that, the raga picks up, in both structural and orchestral complexity; we hear a tabla driving the meter of the song. This track is perhaps most typical of the structure of a classical Carnatic-Dravidian song.

Example B, a Bhajan from Uttar Pradesh, North India, is a devotional song or *bhajan*. It has a fairly more complex orchestra with more instruments than

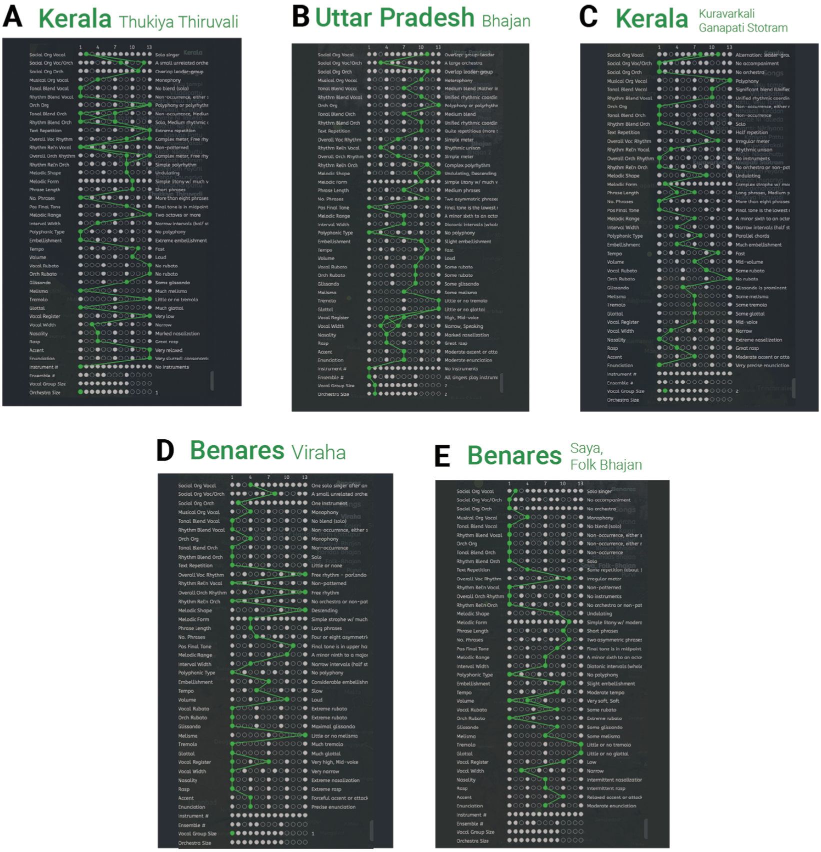

Figure 6 A, B, C, D, and E are screenshots from the Global Jukebox showing full codings for the 37 Cantometric features for each recording[1].

example A. The vocals consist of a group-leader overlap in rhythmic unison.

Example C is also a song from Kerala and is written in praise of the god Ganapati. This track has no orchestra. The absence of an orchestra is perhaps why it is so distanced from example A in the PCA plot in Fig. 5. The song has an alternating style between the leader and group in irregular meter. While the singing is embellished, there is little tremolo, melisma and glottal shake. While more vocally complex than track B, it has relatively simple vocals when compared to example D.

Example D, *Viraha* from Benaras, Uttar Pradesh, is a milking song with tragic overtones, sung with a Nagara drum as accompaniment. Two women alternate singing embellished descending melodic lines in slow tempo. The simple strophe, long phrases, asymmetrical phrases and extreme rubato, sung in a high, tense, nasal, raspy voice give it great complexity. Its vocal style is more elaborate than example B, despite being more or less on the same end of the spectrum in terms of orchestral complexity.

Example E is another *bhajan* from Benaras, Uttar Pradesh. The song has simple, short phrases with a slightly high melodic range and little ornamentation. The register is narrow, and the vocals are quite relaxed. It is similar to track C in its lack of an orchestra, irregular meter, undulating melody, and other orchestral dependant features. Many of these features are quasi-redundant, which may be a reason why tracks E and C are close to each other on the plot, but are musically quite different. The distinction becomes more relevant in our revised PCA in section 2.2.1 (Fig. 7).

2.2.1 PCA re-analysis

Several Cantometric features have quasi-redundancies built in, which may affect the correlation structure found in the PCA. For example, when a song is coded as having no instrumental accompaniment for Line 7 (musical organization of the orchestra, cf. Table 1), it must necessarily also be coded as having no instrumental accompaniment for Line 8 (tonal blend of the orchestra). Similarly, redundancies apply for songs coded as solo singing, such as for Line 4 (musical organization of the vocal part) and Line 5 (tonal blend of the vocal group).

To determine whether this affected our PCA, we repeated the PCA using only a subset of 26 features after excluding the 11 quasi-redundant features (Fig. 7; cf. Table S1 for full list of quasi-redundant features).

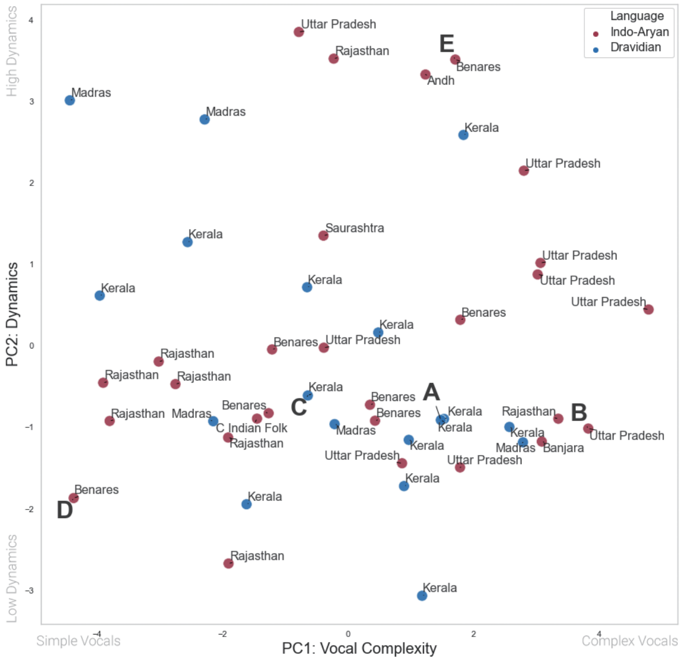

Figure 7 **We repeat the PCA in Fig. 4 using only a subset of 26 features after excluding 11 quasi-redundant features (cf. Table S1 for a list of specific features included/ excluded).**

As in Fig. 4, the revised PCA in Fig. 7 shows no sign of any Indo-Aryan vs. Dravidian clustering. PC1 explained ~20% of the variance and PC2 explained ~11%. Analysis of the variable loadings (Table S2) suggests that PC1 remains interpretable as "vocal complexity", but the second component now appears to capture "dynamics" rather than "orchestral complexity". Specifically, many of the same features as in the previous analysis (repetition of text, tremolo, melodic form, number of phrases, and vocal rubato) still have the highest loadings with PC1, however they are less characterized by vocal features and more by overall musical structure. We can see that recordings A and B are quite similar in terms of musical structure, and hence align closely along PC1. It may be a coincidence that these are both devotional/religious songs, but it would be worth investigating to see if devotional songs follow some common patterns in musical structure. The one instrumental feature retained (musical organization of the orchestra) also maintains a high loading on PC2, but now includes a number of other features related to dynamics (vocal pitch, melodic range, accent and overall rhythm and tempo). Thus, in the revised analysis, PC2 may be better interpreted as “dynamics”. Recording E shows a high degree of variation in this regard, as it is fast, loud and has a melodic range of over two octaves. In contrast, recordings B, C, D and E are relatively simple.

2.3 Within and between society diversity

Analysis of Molecular Variance (AMOVA) (Excoffier et al., 1992) is a technique for quantifying variation within and between populations. It was originally designed for population genetics, but has been adapted to cultural domains including music and folklore (Rzeszutek et al., 2012; Ross et al., 2013) by treating specific combinations of cultural features as analogous to a genetic haplotype (specific combination of genetic variants). Here the populations are the societies in our sample. The AMOVA framework can accommodate multiple levels of structure - here we conducted our analysis using units of song (lowest level), society (next level, e.g., ethnolinguistically defined cultural group such as *Kullu, Kerala* or *Gond*[2)]), and language family (highest level).

We used R’s ade4 package to produce the analysis below (Thioulouse et al., 2007). The matrix of distances between songs was calculated by taking the euclidean distance between all features of recordings. For this analysis we excluded 8 societies represented by only a single song (Central Indian Folk, Santhal Munda, Saurashtra, Bhil, Banjara, Andh, Jhodia and Portuguese Goa) because they would not allow us to quantify within-society diversity.

The results of the AMOVA analysis are shown in Table 2A below. The degree of variation within societies was approximately three times greater than the degree of variation between societies, and only a very minor average difference between Indo-Aryan and Dravidian regions was observed. Only ~1% of all variation among songs in the sample could be explained by differences between language families, while ~25% of variation could be explained by differences among societies within language families). Interestingly, while the proportion of variation between families remains ~1% when analyzing only the subsample of non-tribal, non-Austro-Asiatic-speaking societies, the proportion of variation between societies within families for this subset analysis is approximately five times smaller than it is for the full sample (Table 2B). When this analysis was repeated using only the 26 independent Cantometrics, the resulting amount of between-society variation was intermediate between the other two analysis methods (~11%; Table 2C).

Table 2 2A is an AMOVA of *N*=200 recordings from 3 Indian language families and 25 societies after removing societies where there is only one sample per society. 2B is an AMOVA of *N*=47 recordings from 2 Indian language families and 9 societies. Here we also remove societies where only one sample is present. 2C is the same analysis *N*=47 recordings from 9 societies on 26 features (See Fig. 7 for PCA).

2A. Analysis of Molecular Variance (AMOVA) for Cantometrics in India

Results				**Component of Covariance**		
	Degrees of freedom	Sum Sq.	Mean Sq.		Sigma	%
Between language families	2	20.76	10.38	Variation between language families	0.032	1.33
Between societies within language families	22	141.91	6.45	Variation between societies within language families	0.61	25.21
Within societies	175	312.38	1.79	Variation within societies	1.79	73.46
Total (*N-1*)	199	475.05	2.39	Total variation	2.43	100

2B. AMOVA for non-tribal Dravidian/Indo-Aryan Cantometrics in subsample India

Results				Component of Covariance		
	Degrees of freedom	Sum Sq.	Mean Sq.		Sigma	%
Between language families	1	4.42	4.43	Variation between language families	0.015	0.523
Between societies within language families	7	22.70	3.24	Variation between societies within language families	0.148	5.271
Within societies	38	100.54	2.64	Variation within societies	2.646	94.21
Total (*N-1*)	46	127.67	2.77	Total variation	2.808	100

2C. AMOVA for non-tribal Dravidian/Indo-Aryan Cantometrics in subsample India with a subset of features

Results				Component of Covariance		
	Degrees of freedom	Sum Sq.	Mean Sq.		Sigma	%
Between language families	1	2.35	2.36	Variation between language families	-0.03	-2.107
Between societies within language families	7	15	2.14	Variation between societies within language families	0.17	10.64
Within societies	38	55.38	1.46	Variation within societies	1.46	91.46
Total (*N-1*)	46	72.75	1.58	Total variation	1.59	100

3　Discussion

3.1　Correlated variation among Cantometric features

Our PCA analyses showed that many Cantometric features captured correlated aspects of musical variation. The strongest covariation appeared to correspond to the structural complexity of the vocal part, ranging from complexly ornamented solo singing to simple, repetitive group singing. This component consistently appeared as the first PC in all three analyses (full sample, sub-sample, and subset of variables), consistent with Lomax's claim that many aspects of vocal style tend to consistently covary throughout the world (Lomax, 1980). The second strongest component appeared to be explained by instrumentation and/or dynamics, but this second PC was more variable in the three different analyses, suggesting it may be more sensitive to the particular makeup of the sample and analysis methods.

3.2 Variation within and between societies

Our analysis of musical variation showed that variation within societies was greater than variation between societies, and that average differences between language families in our Indian sample were negligible (~1%). This is consistent with previous studies finding greater musical variation within societies than between them (Rzeszutek et al., 2012; Mehr et al., 2019). However, the degree of variation within societies varied substantially depending on the precise nature of the sample, with only ~5% of variation between societies for the sub-sample of non-tribal, non-Austro-Asiatic-speaking societies vs. ~25% for the full sample and ~11% for an alternative analysis using only the 26 Cantometric features that are not partially dependent on other features. This suggests that the relative degrees of within vs. between society diversity can be strongly affected by the nature of the sample and analysis methods, and thus any general conclusions about within vs. between society diversity may be premature until we can analyse a full global sample.

3.3 Limitations of this study

This study aimed to explore large-scale questions using a restricted set of Cantometric data from a single nation, so all general conclusions should be treated as preliminary.

Even within India, the Cantometric sample is not representative of the Indian populace in general. There is a high proportion of tribal music, and almost all songs are folk songs. The linguistic distribution of peoples in our musical sample is not proportional to the demographic proportion of people living in India. One way to address this is to add new samples that balance out the number of tribal cultures with non-tribal cultures, and also introduce modern folk and classical music.

Analogies with genetics and language also come with caveats. While such analogies have been helpful for developing theories and methods to address cross-cultural musical diversity and change, it is important to remember that each domain has its own unique mechanisms and dynamics that may not necessarily apply to the other domains (Savage, 2019). In particular, while this analysis has adapted methods of quantifying diversity originally developed for population genetics and later adapted to music and other cultural domains, the assumptions of these methods have not yet been rigorously tested for music. Future studies should explore these more rigorously, including exploring the degrees to which different musical features may vary more or less within and between societies. Other areas worth exploring include using more fine-grained analysis of linguistic relationships beyond simply language family classifications, and also other types of cultural classifications that do not rely only on language.

It is important to emphasize that this is an analysis of Cantometric ratings, not the audio sample of the music itself. Future analyses should apply automatic MIR methods such as feature extraction and machine learning in tandem with these Cantometrics ratings to investigate how the audio recordings of the music compares with Cantometrics codings and use the Cantometric codings as training data to develop machine learning methods that can be applied to non-Western musical examples (cf. Panteli et al., 2017; Panteli et al., 2018; Daikoku et al., 2020).

Lomax noted that Cantometric variables would need to be refined and, in some cases omitted, for intra-area analyses. This approach could be used to investigate what features of music link cultures and areas together. Looking at the nature of musical variation within cultures, one may find that here are similar patterns of variation within songs of the same area. Cantometrics has uncovered many of the common characteristics of folk songs in each region and the musicological thread that ties regions together. Future work would entail broadening and refining such connections, for instance, by exploring how perceptual ratings from expert Cantometrics coders can weigh certain acoustic properties over others in determining how styles are linked with each other.

3.4 Implications for Indian music

The fact that our analysis found only minor differences between northern vs. southern Indian music as a whole, but substantial differences between different societies within these regions, suggests that while the division of Indian classical music into northern (Hindustani) and southern (Carnatic) music may be useful for dealing with nuances of the classical traditions, a north-south distinction is an oversimplification that is not useful when considering variation in traditional music throughout India as a whole.

Having grown up in New Delhi, our first author was primarily exposed to North Indian classical music, but his relationship with music was primarily functional. Different songs were sung for formal occasions, weddings and performances, but were collectively deemed 'Hindustani' music. When he visited his mother's extended family in Kerala and Chennai, he could instantly tell there was a difference in the style of Carnatic music, but in retrospect found those differences to be driven by language and context, more so than style and musicality. Religion was perhaps the main unifying factor in all of it, a thread that tied different styles together by a unifying mythos of the *Ramayana* and *Mahabharata*. He attended a few guest workshops by regional artists, mostly from *Rajasthan* and Orissa. He heard styles and instruments he had never heard of before. He was taught that music was primarily ceremonial, and styles would differ greatly depending on one's *guru*. The degrees of variation we find in our results make logical sense if there is that much diversity in a single society of music.

The question of within vs. between culture variation is also important from an empirical point of view, as all classification algorithms attempt at learning embeddings where inter-cultural distance is maximum and intra-cultural distance is minimum. Supervised metric learning algorithms such as LMNN or semi-supervised algorithms such as ITML (Weinberger et al, 2009) are predicated on optimizing within vs. between group variation. Modeling variation in expert-annotated Cantometrics data may help develop analytical tools to help musicologists annotate and classify music at scale. In that respect, an expanded global analysis of within vs. between culture variation would be crucial, ideally including both traditional and contemporary music.

By applying statistical methods to a case study of Cantometric data from India, we have shown how it is possible to quantify and compare variation within and between societies to inform our understanding of musical diversity and apply it to practical tools for computational and comparative musicology. Now that once Cantometric data from throughout the globe will be publicly available, it will be possible to build upon Lomax's original work with these. One can then expand these types of analyses to further our understanding of cross-cultural musical diversity and its implications for society. Although this case study of diversity within traditional songs from a single nation cannot make strong conclusions regarding global patterns of musical diversity, it highlights ways in which future research can be usefully expanded to global scales.

Data/code availability

Code and data can be found at https://github.com/comp-music-lab/sfc-journal-2020. This private repository will be made public when Wood et al. (In prep.) release the full Global Jukebox data (estimated for 2021).

Author contributions

Conceptualization/ Methodology: PES, HD, ALCW; Analysis/ Investigation/ Visualization: HD, PES; Project administration/ Supervision/ Funding acquisition: PES; Writing – original draft: HD; Writing – review & editing: PES, ALCW.

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Supplementary material

Table S1 Features categories

Line Number	Variable name	Category	Redundancy
1	THE SOCIAL ORGANIZATION OF THE VOCAL GROUP	Vocal texture	Quasi-redundant (with 4)
2	RELATIONSHIP OF ORCHESTRA TO VOCAL PARTS	Instrumentation	Quasi-redundant (with 7)
3	SOCIAL ORGANIZATION OF THE ORCHESTRA	Instrumentation	Quasi-redundant (with 7)
4	MUSICAL ORGANIZATION OF THE VOCAL PART	Vocal texture	Independent
5	TONAL BLEND OF THE VOCAL GROUP	Vocal blend	Quasi-redundant (with 4)
6	RHYTHMIC COORDINATION OF THE VOCAL GROUP	Vocal blend	Quasi-redundant (with 4)
7	MUSICAL ORGANIZATION OF THE ORCHESTRA	Instrumentation	Independent
8	TONAL BLEND OF THE ORCHESTRA	Instrumentation	Quasi-redundant (with 7)
9	RHYTHMIC COORDINATION OF THE ORCHESTRA	Instrumentation	Quasi-redundant (with 7)
10	REPETITION OF TEXT	Articulation	Independent
11	OVERALL RHYTHM: VOCAL	Rhythm	Independent
12	RHYTHMIC RELATIONSHIP WITHIN THE VOCAL GROUP	Vocal texture	Independent
13	OVERALL RHYTHM: ORCHESTRA	Instrumentation	Quasi-redundant (with 7)
14	RHYTHMIC RELATIONSHIP WITHIN THE ORCHESTRA	Instrumentation	Quasi-redundant (with 7)
15	MELODIC SHAPE	Melody	Independent
16	MELODIC FORM	Form	Independent
17	PHRASE LENGTH	Form	Independent
18	NUMBER OF PHRASES	Form	Independent
19	POSITION OF FINAL TONE	Melody	Independent
20	MELODIC RANGE	Melody	Independent

21	INTERVAL SIZE	Melody	Independent
22	POLYPHONIC TYPE	Vocal texture	Quasi-redundant (with 4)
23	EMBELLISHMENT	Ornamentation	Independent
24	TEMPO	Rhythm	Independent
25	VOLUME	Dynamics	Independent
26	RUBATO: VOCAL	Rhythm	Independent
27	RUBATO: ORCHESTRA	Instrumentation	Quasi-redundant (with 7)
28	GLISSANDO	Ornamentation	Independent
29	MELISMA	Ornamentation	Independent
30	TREMOLO	Ornamentation	Independent
31	GLOTTAL	Ornamentation	Independent
32	VOCAL PITCH (REGISTER)	Dynamics	Independent
33	VOCAL WIDTH	Vocal tension	Independent
34	NASALITY	Vocal tension	Independent
35	RASP	Vocal tension	Independent
36	ACCENT	Dynamics	Independent
37	ENUNCIATION	Articulation	Independent

Table S2　Variable Loadings of revised PCA (Fig. 7)

Variable	**PC1**	**PC2**
OVERALL RHYTHM: VOCAL	0.12	-0.32
POSITION OF FINAL TONE	0.08	-0.26
MELODIC RANGE	0.03	-0.42
VOLUME	-0.05	0.04
RASP	-0.05	-0.31
MUSICAL ORGANIZATION OF THE ORCHESTRA	-0.09	0.09
MELODIC SHAPE	-0.11	-0.16
MELISMA	-0.14	0.13
TEMPO	-0.16	0.31
VOCAL PITCH (REGISTER)	-0.16	-0.35
GLOTTAL	-0.18	-0.05

NASALITY	-0.18	-0.21
ENUNCIATION	-0.18	-0.05
MUSICAL ORGANIZATION OF THE VOCAL PART	-0.19	0.020
VOCAL WIDTH	-0.19	-0.27
ACCENT	-0.19	-0.31
INTERVAL SIZE	-0.24	-0.05
EMBELLISHMENT	-0.24	0.05
PHRASE LENGTH	-0.25	-0.03
NUMBER OF PHRASES	-0.25	0.13
RUBATO: VOCAL	-0.27	0.19
GLISSANDO	-0.28	-0.07
MELODIC FORM	-0.30	0.06
REPETITION OF TEXT	-0.31	0.04
TREMOLO	-0.31	0.04

Endnote

1) Audio recordings available for A, B, C, D and E respectively under the following links:
A: https://theglobaljukebox.org/#?share=songDetails_Kerala_Thukkiya%20Thiruvadi
B: https://theglobaljukebox.org/#?share=songDetails_Uttar-Pradesh_Bhajan
C: https://theglobaljukebox.org/#?share=songDetails_Kerala_Kuravarkali:%20Ganapati%20Stotram
D: https://theglobaljukebox.org/#?share=songDetails_Benares_Viraha
E: https://theglobaljukebox.org/#?share=songDetails_Benares_Saya,%20Folk-Bhajan
2) Note that while Kullu is a city, Kerala is a state and the Gond are a people. The term "society"is equivalent to 'culture' as it was used in Cantometrics, in which musical samples represented cultures, which in turn were matched to societies described by George P. Murdock in his Ethnographic Atlas.

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