MINING MUSICAL TRAITS OF SOCIAL FUNCTIONS IN NATIVE AMERICAN MUSIC

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ABSTRACT

Native American music is perhaps one of the most documented repertoires of indigenous folk music, being the subject of empirical ethnomusicological analyses for significant portions of the early 20th century. However, it has been largely neglected in more recent computational research, partly due to a lack of encoded data. In this paper we use the symbolic encoding of Frances Densmore's collection of over 2000 songs, digitized between 1998 and 2014, to examine the relationship between internal musical features and social function. More specifically, this paper applies contrast data mining to discover global feature patterns that describe generalized social functions. Extracted patterns are discussed with reference to early ethnomusicological work and recent approaches to music, emotion, and ethology. A more general aim of this paper is to provide a methodology in which contrast data mining can be used to further examine the interactions between musical features and external factors such as social function, geography, language, and emotion.

1. INTRODUCTION

Studying "musical universals" in the context of contemporary theories of music evolution, Savage *et al.* [23] argue that many of the most common features across musical cultures serve as a way of facilitating social cohesion and group bonding (see also [2, 18]). The focus of their analysis, however, is on comparing geographical regions without systematically differentiating between social contexts and functions of music making. Across these regions, the authors look for links and elements of "sameness". The application and methodology presented here can be viewed as complementary to the earlier study [23]. Firstly, we focus on the relationship between internal musical features (such as pitch range, melodic or rhythmic variability) and the specific social function ascribed to songs rather than feature distributions across geographic regions. Secondly, using computational techniques we study features that can *contrast* between different social functions within a culture, rather than those that are potentially *universal* in music.

The folk songs of Native American groups provide a convenient starting point for the analysis of social function and musical features: a large number of pieces has been recorded by (relatively few) individuals who often annotated the music with an explicit social function. Nettl commented in 1954 that "more musical material [was] available from this large area [...] than from any other of similar size" [20, p. 45]. The collection created by Frances Densmore [25] covers repertoires from five out of the six musical areas postulated by Nettl. Densmore collected songs by Native American groups (see Table 1), and recorded the social usage of songs, ranging from the general (e.g. war songs) to the specific (e.g. songs of the corn dance). Building on Densmore's work, Herzog [10] discussed four categories of social function in music of the North American Plains, specifically love songs, songs of hiding games, ghost dance songs, and songs in animal stories. Employing quantitative analysis, Gundlach also compared songs used in different situations, e.g. war songs or healing songs; groups of songs were taken as proxies for studying mood, specifically asking if "objective characteristics of a piece of music form the basis for the mood which it may arouse" [7, pp. 134-135]. Interestingly, Gundlach found a diversity in the treatment of some musical features to convey emotion across indigenous groups, such as larger intervals mainly associated with "sad" love songs among the Chippewa and Ojibway but with "happy" love songs among the Teton-Sioux [7, p. 139].

This paper builds upon Gundlach's work, exploring quantitative analysis to identify musical traits of songs associated with different social functions. More specifically, we adopt contrast data mining [1, 5, 21], a type of descriptive supervised data mining. In the context of music information retrieval, supervised data analysis has been largely dominated by predictive classification, i.e. building models that discriminate labeled groups in data and predict the group label of unseen data instances. Classifiers are generally treated as a black box, and results tend to focus on predictive accuracy. By comparison, contrast data mining aims to discover distinctive patterns which offer an understandable symbolic description of a group.

Discovered patterns are discussed both in light of ethnomusicological writings such as those by Densmore, Herzog and Gundlach, and in the context of research into music and emotion. The music information retrieval community has engaged with models and classifiers of emotion in music from many different perspectives and utilizing a wide range of approaches. For example, Han *et al.* [8] implemented support vector regression to determine musical emotion, and found their model to correlate quite strongly with a two-dimensional model of emotion. Schmidt and Kim used conditional random fields to model a dynamic emotional response to music [24]. For a thorough review of emotional models in music information retrieval, see Kim *et al.* [14], and for an evaluation and taxonomy of the many emotional approaches to music cognition, see Eerola and Vuoskoski [6]. Unlike these studies, the current study does not attempt to model emotion or provide a method of emotion classification, but considers findings from emotion and ethological research in discussing the mining results.

2. THE DENSMORE CORPUS

Frances Densmore's transcriptions of Native American folksongs provide an invaluable dataset with which we might examine issues pertaining to geography, language, and culture. As Nettl points out, many of the earlier recordings were conducted in the very early days of field recording, and contain performances from elderly individuals who had little contact and influence from the Western musical tradition [20]. The fact that this collection was transcribed by a single individual, covers such a large geographic area, and focuses on cultures with disparate social and linguistic norms, makes it immensely useful for studies of large-scale relationships between music and language, geography, and social function.

Interest in digitally encoding Frances Densmore's collection of Native American songs began in the late 1990s, when Paul von Hippel encoded excerpts of the first book of Chippewa songs in 1998 into Humdrum's **kern format. David Huron encoded the Pawnee and Mandan books in 2000, and Craig Sapp encoded the lengthy Teton Sioux book in 2002. In 2014, Eva and Daniel Shanahan encoded the remaining books into **kern format [25]. The digitized collection contains 2,083 folksongs from 16 books (Table 1), collected between 1907 and 1958. [1]

The Densmore volumes provide a rich source of information because they not only give transcriptions of all the collected songs, but also additional information – including the associated social function – and musical analyses. Densmore's annotations were integrated as metadata into the digital collection. As exact phrasings and annotation criteria vary across the chronological span of Densmore's writing, the metadata vocabulary was prepared by cleaning and generalizing social function terms: firstly, inconsistent phrasings were harmonized, e.g. "hand game songs" (Northern Ute book) and "songs of the hand game" (Cheyenne and Arapaho book). Secondly, functions were merged to create generalized functions, e.g. different game songs such as hand game songs and moccasin game songs were collated into one group "game songs" (see Fig. 1).

[1] The corpus is available at musiccog.lsu.edu/densmore

Book	Year published
Chippewa I	1910
Chippewa II	1913
Teton Sioux	1918
Northern Ute	1922
Mandan and Hidatsa	1923
Papago	1929
Pawnee	1929
Menominee	1932
Yuman and Yaqui	1932
Cheyenne and Arapaho	1936
Nootka and Quileute	1939
Indians of British Columbia	1943
Choctaw	1943
Seminole	1956
Acoma, Isleta, Cochiti, and Zuñi Pueblos	1957
Maidu	1958

Table 1. Collections included in the Densmore corpus.

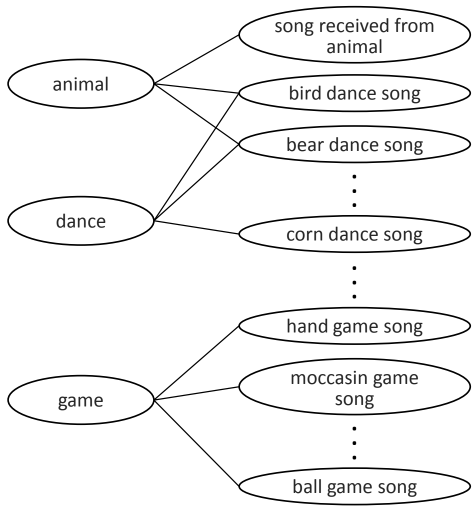

Figure 1. Excerpt of the social functions ontology.

Songs which Densmore listed as "uncategorized" or "miscellaneous" were not considered. The resulting ontology reduces the 223 distinct terms used by Densmore to 31 generalized functions. Note that songs can be assigned more than one function, e.g. bird dance songs are annotated as both "animal" and "dance" (see Fig. 1).

3. CONTRAST DATA MINING

Contrast data mining [1, 5] refers to a range of methods which identify and describe differences between groups in a dataset, and has been applied with success to several folk song corpora [21]. In the current study with the Densmore corpus, groups are defined by songs associated with different social functions. Following several other earlier works on contrast data mining in folk music analysis, in

Attribute	Definition	High (H)	
AverageMelodicInterval	average melodic interval in semitones	$\geq$	1.676
AverageNoteDuration	average duration of notes in seconds	$\geq$	0.347
DirectionofMotion	fraction of melodic intervals that are rising rather than falling	$\geq$	0.388
Duration	total duration of piece in seconds	$\geq$	22.294
DurationofMelodicArcs	average number of notes that separate melodic peaks and troughs	$\geq$	1.704
PitchVariety	number of pitches used at least once	$\geq$	6.583
PrimaryRegister	average MIDI pitch	$\geq$	55.578
Range	difference between highest and lowest MIDI pitches	$\geq$	13.084
RepeatedNotes	fraction of notes that are repeated melodically	$\geq$	0.462
SizeofMelodicArcs	average melodic interval separating the top note of melodic peaks and bottom note of melodic troughs	$\geq$	4.899
StepwiseMotion	fraction of melodic intervals corresponding to a minor or major second	$\geq$	0.250
VariabilityofNoteDuration	standard deviation of note durations in seconds	$\geq$	0.224
DcontRedundancy	duration contour relative redundancy	$\geq$	0.749
DurRedundancy	note duration relative redundancy	$\geq$	0.667
IntRedundancy	melodic interval relative redundancy	$\geq$	0.606
MlRedundancy	metric level relative redundancy	$\geq$	0.681
PcontRedundancy	melodic pitch contour relative redundancy	$\geq$	0.751
PitchRedundancy	pitch relative redundancy	$\geq$	0.603

Table 2. A selection of attributes used in this study. Top: jSymbolic attributes [17]. Bottom: information-theoretic attributes. The rightmost column indicates the value range for the discretisation bin High.

this study songs are described by *global features* which are attribute-value pairs each describing a song by a single value. Global features have been used productively in computational folk music analysis in the areas of classification (e.g. [11, 17, 27]) and descriptive mining (e.g. [16, 26]).

It is important to highlight the distinction between attribute *selection* and contrast data mining. Whereas the former is the process of selecting informative *attributes*, usually for the purposes of classifier construction, contrast data mining is used to discover *particular* attribute-value pairs (features) that have significantly different supports in different groups.

3.1 Global feature representation

All songs in the corpus were converted to a MIDI format, ignoring percussion tracks and extracting one single melodic spine for each song. Since only a fraction of the songs in the corpus were annotated with tempo in the **kern files, all songs were standardized to a tempo of ♩ = 60. This was followed by computing 18 global attributes: twelve attributes from the jSymbolic set [17] and six newly implemented information-theoretic attributes. After discarding attributes not applicable to the current study such as those related to instrumentation, dynamics, or polyphonic texture, the twelve jSymbolic attributes were selected manually, informed by Densmore's own writings, additional ethnomusicological studies of Native American music [7, 10, 20] and research into music and emotions [6, 13, 22]. The six information-theoretic attributes measure the relative redundancy *within a piece* of a particular event attribute (pitch, duration, interval, pitch contour, duration contour, and metric level). The features are defined as $1 - H/H_{\max}$ where H is the entropy of the event attribute in the piece and the maximum entropy $H_{\max}$ is the logarithm of the number of distinct values of the attribute in the piece. The value of relative redundancy therefore ranges from 0 (low redundancy, i.e. high variability) to 1 (high redundancy, i.e. low variability) of the particular attribute. Numeric features were discretized into categorical values, with a split point at the mean: the value Low covers attribute values below the average across the complete dataset, the value High covers attribute values at the average or above (cf. [26]). Table 2 gives definitions for the attributes which contribute to the contrast patterns reported in Section 4.

3.2 Contrast data mining method

Global features are assessed as candidate contrast patterns by evaluating the difference in pattern support between different groups (e.g. [1, 5]). A feature (attribute-value pair) is *supported* by a song if the value of the attribute is true for the song. Then the support $n(X \wedge G)$ of a feature X in a group G is the number of songs in group G which support feature X. A feature is a *contrast pattern* for a certain group if its support in the group, $n(X \wedge G)$, is significantly higher or lower than in the remaining groups taken together, $n(X \wedge \neg G)$. This is known as a *one-vs.-all strategy* for contrast mining [5, 21] as it contrasts one group against the combined set of other groups rather than contrasting groups in pairs. The significance of a pattern, that is, how surprising is the under- or over-representation of X in G, can be quantified using the hypergeometric distribution (equivalent to *Fisher's exact test*). This uses a 2×2 contingency table (see Table 3) which gives the

	G	$\neg G$	
X	$n(X \wedge G)$	$n(X \wedge \neg G)$	$n(X)$
$\neg X$	$n(\neg X \wedge G)$	$n(\neg X \wedge \neg G)$	$n(\neg X)$
	$n(G)$	$n(\neg G)$	N

Table 3. Contingency table showing the occurrence of a pattern X and its complement $\neg X$ in a target group G and in the background $\neg G$. The highlighted area is the support of the putative contrast pattern $X \wedge G$. For the Densmore corpus $N = 2083$.

probability of sampling $n(X)$ pieces, and finding exactly $n(X \wedge G)$ successes (instances of group G). Thus the left or right tails of the hypergeometric distribution give the two desired p-values: the probability of observing at most or at least $n(X \wedge G)$ instances in a single random sample of $n(X)$ instances. A low p-value, less than some specified significance level α, indicates a statistically significant contrast pattern which is assumed to be interesting for further exploration [3].

Following the extraction of features as described in Section 3.1, each song in the corpus is represented by a set of global features together with a set of group labels (functions) of the song. Note that, as mentioned above, more than one function can be assigned to a song. From this input dataset candidate patterns are generated as the cross-product for all occurring pairs of features X and groups G. For each $X \wedge G$ pair its support and a p-value for each tail are computed and the results processed to form a matrix of function/feature patterns.

4. RESULTS AND DISCUSSION

A total of 17 social function groups (uncategorized and miscellaneous songs and groups supported by less than ten songs were not considered) were mined for contrast pairs with 18 attributes. The 17 groups together cover most of the corpus: 1891 of the 2083 songs. Regarding the attributes for global features, though each has two possible values High (H) and Low (L), if one is significantly over-represented the other must be significantly under-represented, therefore in this study only the High value was considered during mining. Table 4 presents the results of the contrast data mining. Each cell in the matrix shows the distribution of a particular feature in a particular group. White indicates presence of the feature in the group (with area $n(X \wedge G)$) and black absence (with area $n(\neg X \wedge G)$). Thus the total area covered by a cell in a row indexed by group G is $n(G)$. The rows and columns in the table are ordered by the geometric mean of the p-value to all other functions or features in that particular row or column.

Statistical significance of each contrast pattern was evaluated using the hypergeometric distribution as described above, with significance level $\alpha = 0.05$ adjusted using a Bonferroni multiple testing correction factor of $306 = 17 \times 18$, representing the number of contrast patterns tested for significance. Using the adjusted significance level of $0.05/306$ =1.6e-4, green areas in Table 4 indicate significant over-representation, and red areas significant under-representation of a feature in a group. A total of 56 significant patterns were found (colored patterns of Table 4).

As a statistical control, a permutation method was used to estimate the false discovery rate, assuming that most contrast patterns found in randomized data would be artifactual. Social function labels were randomly redistributed over songs, while maintaining the overall function counts, then the number of significant (left or right tail p-value $\leq$ 1.6e-4) contrast patterns using the 306 possible pairs was counted. Repeated 1000 times, this produced a mean of just 1.14 significant contrast patterns per iteration, suggesting that there are few false discoveries to be expected in the colored patterns of Table 4.

Bearing in mind that the exact data samples and feature definitions differ, the results seem to confirm – and generalize to a larger dataset – several observations presented in earlier studies. The significance of PrimaryRegister : H for love songs recalls Gundlach's finding that "love songs tend to be high" [7, p. 138]. Herzog describes the "melodic make-up" of love songs as "spacious" [10, p. 28]: in our analysis we find that love songs generally have larger average melodic intervals and a wider range than other songs. The over-representation of AverageNoteDuration : H in love songs may reflect characterisations of love songs as slow [7, 10]. For hiding game songs of the Plains, Herzog notices that they are comparatively short with a very often limited range [10, p. 29]; game songs in the current corpus – including 90 out of the 143 game songs explicitly associated with hiding games such as moccasin, hand and hiding-stick or hiding-bones games – show a significant under-representation of Duration : H and Range : H. The narrow range that Gundlach observed in healing songs [7, pp. 138,140] is also reflected in the results in Table 4, but in the current analysis is not statistically significant. Gundlach compared healing songs specifically against war and love songs: considering only those two groups as the background does indeed lead to a lower p-value (left-tail) for Range : H in healing songs (6.8e-9 instead of 2.6e-3). Together with other traits which are common in healing songs but not distinctive from other song types — e.g. a high proportion of repeated notes and low variability in pitch, intervals or duration — a comparatively narrow range may contribute to a soothing character of many healing songs, intended "to remove discomfort" [4, p. 565].

The information-theoretic features are particularly characteristic of songs labelled as "nature", which show an over-representation of redundancy values above the average for all six considered event attributes. The group contains 13 Yuman lightning songs, which trace the journey of White Cloud who controls lightning, thunder and storms. More generally, Yuman songs tend to be of comparatively small range, the melodic movement on the whole mainly descending, the rhythm dominated by few duration values and isometric organisation more common than in other repertoires [9,20]; structurally, Yuman music is often based on repeated motifs [9]. The example of the Yuman light-

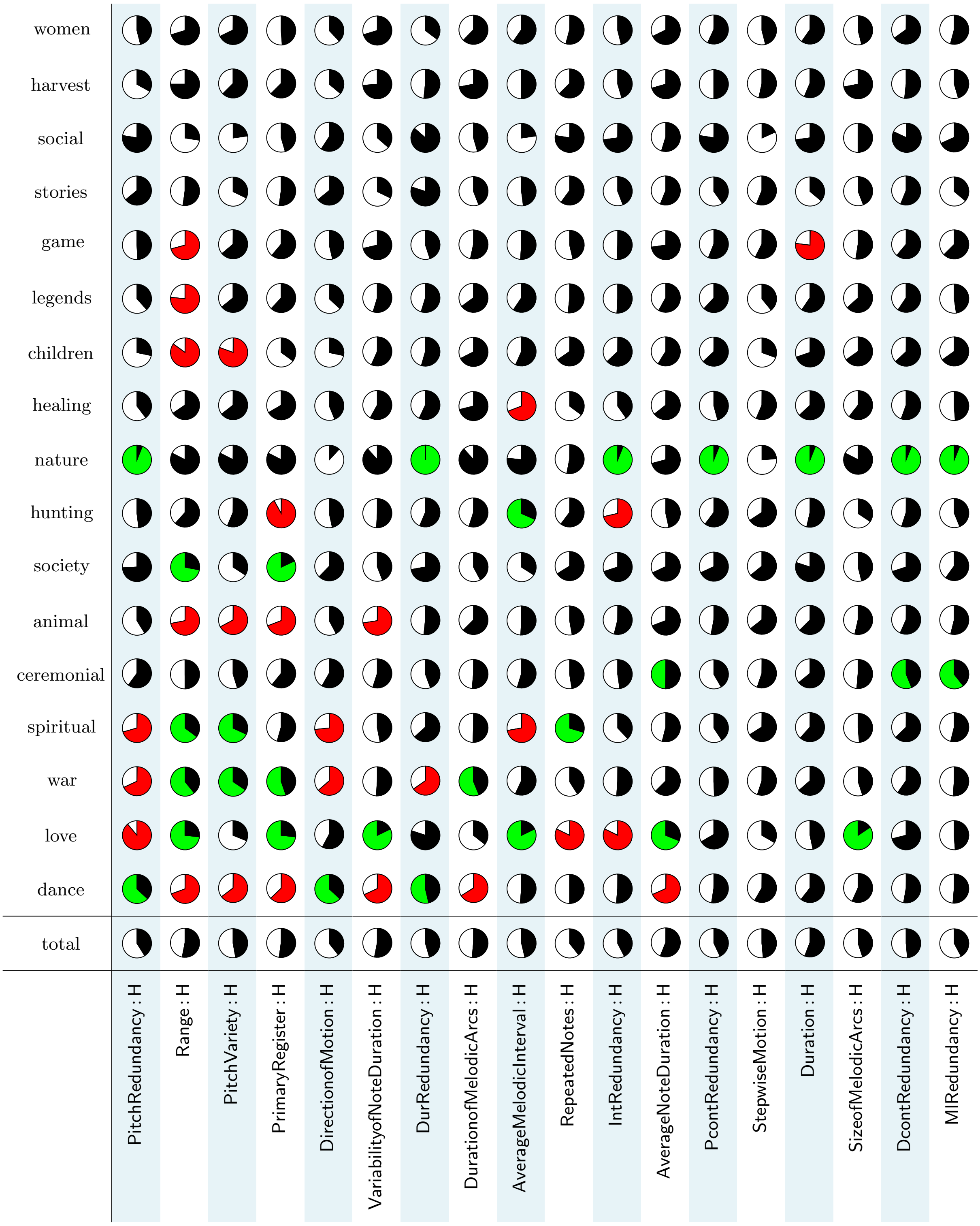

Table 4. Pie charts for contrast patterns showing the distribution of social function groups (rows) against features (columns). White indicates presence and black absence of the corresponding feature. Green/red (light/dark gray in grayscale) indicate significant over/under-representation of a feature in a group.

ning songs opens avenues for future analysis, such as considering also sequential pattern mining [3], and encourages applying data mining to questions left unanswered in earlier work, such as exploring the stylistic unity of songs forming a series related to a myth or ritual [9, p. 184].

It can be productive to discuss the mining results in the context of recent work that takes an "ethological" approach to music and emotion. This approach argues that pitch height, tempo, dynamics, and variability convey levels of both arousal and valence, and many of these relationships are innate, cross-cultural, and cross-species [12, 13, 19]. Similarly to Gundlach's earlier work [7], we find that war songs and love songs exhibit several salient musical traits. In the Densmore collection, war songs are distinguished from other song types by significant over-representation of a wider than average range, higher than average register, and higher variability in both pitch and duration (over-representation of PitchVariety : H and under-representation of PitchRedundancy : H and DurRedundancy : H). Interestingly, dance songs also show significant contrasts in these features, but consistently in the opposite direction compared to war songs. War songs and dance songs might both be thought of as "high arousal", but on opposite ends of the valence spectrum on Russell's Circumplex model [22]. This hypothesis invites further inspection of war and dance songs in the corpus. Significant features shared between dance and animal songs (Range : H, PitchVariety : H, PrimaryRegister : H and VariabilityofNoteDuration : H being under-represented) reflect the fact that many of the supporting songs – e.g. bird, bear or deer dance songs – are annotated with both "dance" and "animal" (see also Fig. 1).

In love songs, the over-representation of higher pitch registers, observed both by Gundlach and in the current study, seems in line with Huron's acoustic ethological model [13], according to which higher pitches (alongside quiet dynamics) connote affiliation. For a Pawnee love song Densmore relates her informant's explanation that in this song a married couple for the first time openly expressed affection for each other. Both Densmore and Gundlach characterize many love songs as "sad", associated with departure, loss, longing or disappointment, which might be reflected in the relatively slow movement of many love songs (see above). Remarkably, though, at first inspection other contrast patterns describing love songs (e.g. under-representation of IntRedundancy : H or over-representation of PrimaryRegister : H) seem at odds with findings on e.g. sad speech which contains markers of low arousal such as weak intervallic variability and lower pitch [15]. However, when comparing observations across studies, their specific feature definitions and analysis methods need to be taken into account. In the current study, significant contrast features are discovered relative to the feature distributions in the dataset, both in terms of feature values and thus the mean value in the corpus (used in discretizing global features into values Low and High), and occurrence across groups (used in evaluating significant over- or under-representation during contrast mining).

5. CONCLUSIONS

This paper has presented the use of descriptive contrast pattern mining to identify features which distinguish between Native American songs associated with different social functions. Descriptive mining is often used for explorative analysis, as opposed to statistical hypothesis testing or predictive classification. Illustrating contrast pattern mining in an application to the Densmore collection, results suggest musical traits which describe contrasts between musics in different social contexts. Different from studies focusing on putative musical universals [23], which test generalized features with disjunctive values (e.g. two- or three-beat subdivisions), and from attribute selection studies [27], which do not specify distinctive values, global-feature contrast patterns make explicit an attribute and value pair which is distinctive for a certain song type. In this case study, mining results confirm findings of earlier ethnomusicological research based on smaller samples, but also generate questions for further investigation.

The Densmore corpus of Native American music provides a rich resource for studying relations between internal musical features and contextual aspects of songs, including not only their social function but also e.g. languages and language families [25], geographical or musical areas [20]. Thus, contrast mining of the Densmore collection could be extended to other groupings. Regarding social functions, the ontology used here possibly could be linked to anthropological taxonomies on functions of musical behaviour (e.g. [2, 18]), whose categories on their own are too broad for the purposes of contrast pattern mining but could open additional interpretations if integrated into hierarchical, multi-level, mining. Regarding pattern representations, the method of contrast data mining is very general and in theory any logical predicate can be used to describe groups of songs. For future work we intend to explore the use of sequential melodic patterns to describe social functions in the Densmore corpus, and also to apply the methods to other large folk song collections.

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