Analysis of Humpback Whale Songs: Applying the traditional method

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ABSTRACT

Humpback whale songs consist of a series of complex vocalizations. These songs consist of units, the shortest audible sound, a series of units making up a phrase, a series of phrases making up a theme, and a series of themes making up a song. An individual song can last up to 30 minutes and be repeated up to 24 hours. A hydrophone, a form of passive acoustic monitoring, located in the Monterey Bay National Marine Sanctuary recorded the humpback songs from October 2015 to April 2017. My mentor, John Ryan, decimated and normalized 429 songs, which served as my data set. Applying the traditional method, I manually isolated and analyzed 10 out of the 429 songs in the data set and identified 26 distinct unit types. I labeled the units based on classification in the literature. Because this method is exceptionally laborious and with the subjective nature of labeling, there is the necessity and attraction of machine learning. Tom Bergamaschi, the intern I collaborated with on this project, explored machine learning methods to investigate a way to automate the isolation of units within a song, distinguishing between signal and noise and subsequently the differentiation of different unit types.

INTRODUCTION

Humpback male whales, or the jazz singers of the sea, are known for their intricate song, which is unique compared to other whale vocalizations in that it is composed of a hierarchical structure. The song consists of units, the shortest audible sound, a series of units which makes up a phrase (15 sec), a series of phrases that make up a theme (2 min), and themes which form a song (Cholewiak *et al.*, 2012; Figure 1 below).

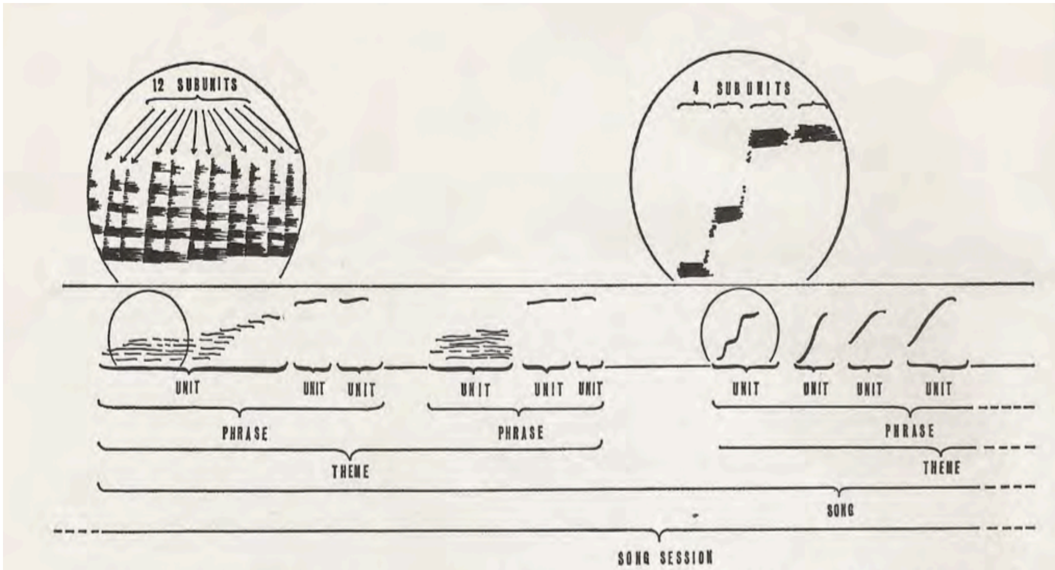

Figure 1: This is a diagram of the hierarchical structure of a humpback whale song.

A single song can last more than 30 minutes and can be repeated for more than twenty-four hours ("Humpback Whale Facts"). Songs consist of percussive or noisy units with changing pitches interspersed with pure tones. Harmonics are prevalent throughout the songs and for our purposes we included both the primary unit and the harmonics as one unit, but for our analysis we focused on the primary or fundamental unit only. Harmonics can reach as high as 24,000 Hertz, further proving the extreme complexity and range of these songs (Au *et al.*, 2006). Their songs would be considered a collection of moans, grunts, gurgles, groans, and cries. Humpbacks from the same region, within a population, are found to sing the same song with slight nuances; however, over time, the song evolves (Janik, 2014). This horizontal transfer of song refers to peers influencing the transfer of song within a population rather than vertical transfer of song in which the mother passes traits to offspring (Garland *et al.*, 2011). Male humpbacks in the North Atlantic can be found singing identical songs in unison miles away from one another, while whales in the North Pacific sing a completely different song. Due to the whales' migration from Western Australia to Eastern Australia, the resident whales of Eastern Australia completely replaced their song (Garland *et al.*, 2011). As one whale incorporates new units, phrases, and themes into his song, the new song spreads throughout the community. Since whales are solitary creatures, they are often found singing alone, but it is not uncommon to hear or see whales singing in the presence of other whales (Cholewiak *et al.*, 2012).

Because males are the ones singing, it can be assumed that the songs are a form of courtship during the mating season (Cholewiak *et al.*, 2012). There are several theories as to what the song's function is: mating call, threats in response to other males approaching the singer, and possibly sonar to locate other whales. However, it is uncertain whether the songs repel other males and or attract the females directly, intersexual and intrasexual communication (Cholewiak *et al.*, 2018). The females are polygamous, but ultimately it is the females decision on who she mates with. The mating season occurs during the winter months, while foraging and migration occur during summer. These whales can migrate up to 3,000 miles. Pacific humpbacks generally feed in Alaska, Eastern Russia, and British Columbia, while they migrate to tropical waters such as Hawaii, Central America, Mexico, or Asia in the winter to breed and give birth (Torode, 2018).

Humpbacks have been found singing during foraging, leading to more questions (Stimpert *et al.*, 2012). It has been concluded that singing during foraging allows them to maintain acoustic contact during migration (Norris *et al.*, 1999). Furthermore, courtship may continue and does not seem to be restricted to breeding grounds. Temperature or circumstance may also affect the continuation of song crossing into the feeding grounds.

Social sounds nevertheless can be produced by both females and males to communicate (Janik, 2014). Communication through sounds can occur between mother and calf and for a variety of other reasons. For example when bubble net fishing, humpbacks will create vocal sounds to frighten fish, causing them to swim to the surface ("Humpback Whale Facts"). Also when the whales lose a family member or friend, they'll produce moans or whines which may be confused with a song. While toothed whales use echolocation for navigation and foraging, baleen whales create songs to communicate.

Humpback songs are very similar to the songs of nightingales ("Luscinia megarhynchos: Nightingale - Turdidae"). The unpaired male nightingales sing at night from April-June to attract females. Their songs consist of a compilation of whistles, trills, and gurgles similar to humpback whale songs. Once they find a mate, the males will stop singing during the night and will only sing during the day. Unlike bird song, humpback song will continue, as males may sing to multiple partners. Nightingales are often found singing one hour before sunrise as a way to defend their territory against other males in the vicinity.

How are these sounds created? A humpback whale lacks vocal cords and it is through the larynx that the sound travels from the whale to the ocean (Cholewiak *et al.*, 2012). The frequency range of their songs fluctuates between 20 Hertz and 24,000 Hertz (Au *et al.*, 2006). These songs can travel a minimum of 20 miles away. Estimates of maximum distances over which humpback song can be detected range from ~ 33 km to ~160 km (Norris *et al*., 1999). Source levels of the songs can reach up to 171-189 dB re:1 micropascal (Au *et al.*, 2001). For reference, humans can hear within the frequency range 20-20,000 Hertz so most of the humpback song units are within our range of hearing (Pujol, 2018).

Because of the immense variation and length of a song, it is hard to categorize units. Do we see patterns from year to year, month to month? There is a plethora of questions scientists have about what these songs convey and the structure of these songs over time. As of now, it is certainly more accurate to manually isolate and classify song units, but as that is extremely time consuming and inefficient, Tom Bergamaschi, the intern I collaborated with on this project this summer, worked to find a coherent method to automatically analyze and isolate song units, filtering out the noise. I took the path of the traditional method of manually isolating song units and labeling them according to literature classification. Not only did the papers include spectrograms with which to compare song units, one included audio files to further verify classification of that unit. There are several attempted methods to try and automate the isolation of units.

My labeling served as a "ground truth" in the analysis of humpback song structure. As I only labeled 10 songs, a small sample set out of the 429 songs in the data set, it proves the necessity for machine learning to automate the isolation of units. It took me approximately 4-5 days to label one song, of course depending on the length and complexity of the song. The more songs I labeled, the easier it became because I was familiar with the unit types. If there was low signal to noise ratio, I moved on to another song in my data set. Furthermore, one of the many disadvantages of the traditional method was the subjective nature that the labeling entails.

Machine learning has become the forefront in our society, allowing for increased efficiency if the right algorithm is generated and for science to be conducted in new but challenging ways. Tom decided to implement an unsupervised classification method to isolate humpback song units. To generate any clustering, he had to extract features from the signals (units) with which effective clustering could take place. Latent Dirichlet Allocation (LDA) served as a statistical model, allowing observations to be described by unobserved groups (Blei *et al*., 2003). Realtime Online Spatiotemporal Topics or ROST topic model presented us with a type of statistical model for abstract "topics", or clusters of similar words, in a group of documents (Girdhar *et al*., 2013). We envisioned a song unit to be a collection of documents with a repeated topic distribution with the hopes of being able to distinguish between signal and noise, then differentiate between different unit types. Once we obtained some results from the topic model, we were then able to compare those results with my labeled data set. From there, we'd be able to make modifications to the parameters if necessary and better comprehend how to define a song unit.

MATERIALS AND METHODS

A. RAVEN ANALYSIS

As of July 28, 2015, the Monterey Accelerated Research System (MARS) has recorded these humpback whale songs at a sampling rate of 256 kHz using an Ocean Sonics icListen HF- an omnidirectional hydrophone, or underwater microphone, with a bandwidth of 10 Hz to 200 kHz (Ryan *et al*., 2016). The hydrophone, located 900 meters below the water, is perfectly situated in the Monterey Bay National Marine Sanctuary and generates an ideal soundscape. One of my mentors, John Ryan, decimated and normalized 429 humpback whale songs from October 2015 to April 2017 to serve as my data set. Song distinction was based on a clearly repeated series of themes (Ryan *et al*., in prep).

To conduct my analysis, I used Raven, an interactive sound analysis software, originally created for the Cornell Ornithology lab to analyze bird song (Charif *et al.,* 2010). Raven shows both a waveform and spectrogram for a given song. The waveform shows the amplitude versus time, while the spectrogram shows frequency in Hertz versus time. For my study, only the spectrogram was utilized. Spectrograms serve as a visual representation of the frequencies of sound as they vary in time. They can be created both by fast fourier transform or bandpass filters. The default settings often aren't sufficient to clearly view the spectrogram. Adjusting the contrast and brightness of the spectrogram allows the signals (units) to become more visible and discrete. Also relative power is shown, the default being a grayscale, enabling one to distinguish signals with a darker color and therefore containing more power. Changing window size, or number of samples per frame adjusts the sharpness of the signal. I alternated between 1024, 2048, and 4096, coming to the conclusion that 4096 gave the best results. A large window size tends to produce better frequency display, while a smaller window size produces better time display. Selection tables present below the spectrogram allow for a multitude of measurements to be chosen to show within the table. Measurements I chose were low and high frequency (Hz), start and end time (sec), delta time (difference between start and end time) (sec), peak frequency contour (Hz), aggregate entropy (bits), peak frequency (Hz), and IQR bandwidth (Hz) for each of the units I isolated. Peak frequency measures the frequency at which the maximum power occurs within the unit (Charif *et al.,* 2010). Aggregate entropy measures the disorder in a sound, analyzing the energy distribution within a selection. IQR bandwidth measures the difference between the first and third quartile frequencies. I also included a description column in which I labeled the units based on literature classification.

The songs chosen to label manually were based on their high signal to noise ratio, or the least amount of background noise; these songs were the easiest to identify the song units as the strength of the signal was both loud and clear. I labeled 10 humpback songs, most of which occurred during the winter months (November-January), the time of year when most (>80%) of all humpback song is detected in MARS recordings. After choosing a song, a selection box (active selection) was drawn around the unit and the measurements chosen were recorded in the selection table. I drew boxes as I listened to the signal, further verifying that I captured an accurate frequency range and duration of the unit (Figure 2 below). Unfortunately, the measurements were taken directly from the bounds of the boxes instead of the actual signals themselves, allowing for either an overestimation or underestimation of the data. The selections occurred in numerical order, making it easier to identify certain units. The selection tables were then used for further analysis to observe patterns and song structure.

Units consisted of the primary or fundamental unit and harmonics which could rise above 24,000 Hertz. For our purposes and to make the machine learning analysis easier to process all the data, I chose to focus on the frequency range from 50 to 2,000 Hertz as that range is where I saw the primary units. Harmonics tended to maintain the same overall shape or contour of the primary unit, stacked above the primary unit. However, some primary units were found within the stack of harmonic signals and could be distinguished primarily by listening to the unit. It was quite easy to make accidental selections, but one way to check for these was by skimming through the selection table and noticing any zeros or blanks for certain measurements.

Harmonics, as suggested, are the way the whales produce sounds rather than influences from the environment.

Initially I attempted BLED, or the band limited energy detector within Raven but as there was such great variation in the song, as compared with BLED being used to detect song units from blue and fin whales with less varying units, I didn't proceed further with this detector. Instead I proceeded to manually label songs according to the literature.

B. LABELING UNITS

The three primary papers used to classify the song units were Dunlop, Fournet, and Stimpert. Stimpert's paper focused on the humpback whale's two most stereotyped and distinctive unit types, the wop and grunt (Stimpert *et al.*, 2011; Figure 3 below). I utilized the table with measurements, the waveform and spectrogram, and most important of all, the audio files. In terms of using the measurements, I focused on the average low and high frequencies and delta time in order to classify the units. I was a bit lenient on the low and high frequencies as even the same unit types within a song had slightly different measurements. As there were more than just these two types of units, I turned to two other papers, Dunlop and Fournet.

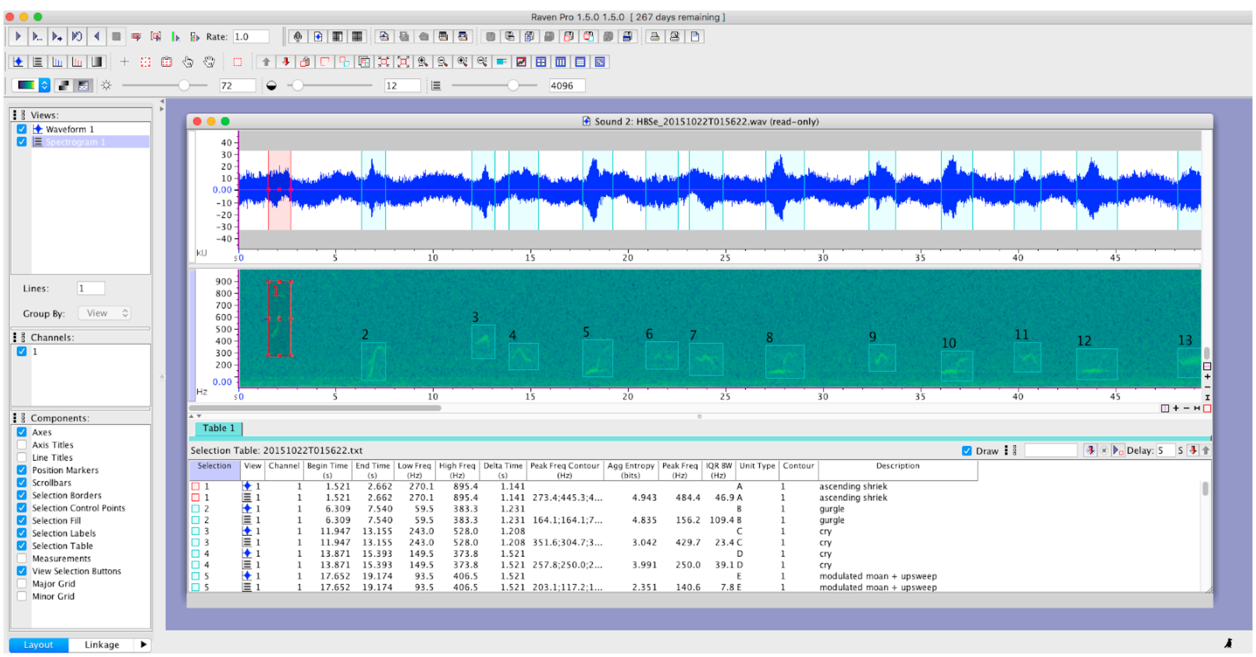

Figure 2: This is a snapshot of Raven and the waveform, spectrogram, and selection table.

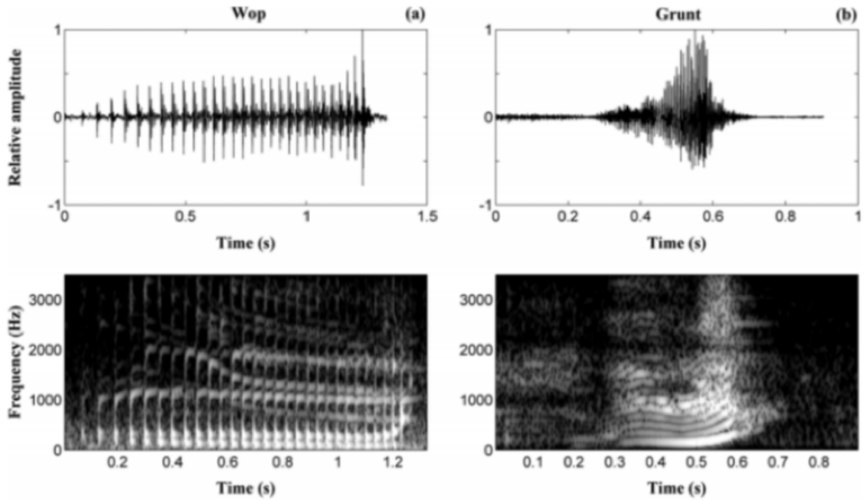

Figure 3: This is the waveform on the top row and spectrogram on bottom row for the wop and grunt (Stimpert et al, 2011).

Dunlop's paper focused on the social vocalization repertoire of east Australian migrating humpback whales (Dunlop *et al.*, 2007). Thirty-four separate call types from a sample of 660 sounds recorded from 61 groups of varying compositions over 3 years were identified in this study, generating a catalog to use when analyzing other songs. A table of mean spectrogram parameters of all the unit types along with sliced spectrograms of all the unit types allowed me to label my ten songs. Again, I concentrated on using the low and high frequencies, delta time, and contour of the units from the spectrogram with which to compare. Dunlop grouped units into the following categories: low-frequency sounds, mid-frequency harmonic sounds, high-frequency harmonic sounds, amplitude-modulated sounds, broadband/ "noisy" and complex sounds, and repetitive sounds.

Fournet's paper focused on the repertoire and classification of non-song calls in Southeast Alaskan humpback whales (Fournet *et al.*, 2015). Sixteen individual call types from a sample of 299 non-song vocalizations collected over a 3-month period were identified in this study under the classification of four vocal groups: low frequency harmonic, tonal, pulsed, and noisy. This paper also included tables with measurements and spectrograms enabling the labeling of units.

RESULTS

After labeling all the units within the ten songs (2015-2017), I identified 26 different unit types. To narrow the number of unit types, I decided on broader unit types. For example, instead of descending moan and ascending moan being 2 different unit types, I classified them as one unit type, moan.

Classes	**Description**	**Unit Labels**
Low Frequency Harmonic	Most energy below 500 Hz, harmonic up to 14,000 Hz	Groan, Moan
Low Frequency	Fundamental below 60 Hz	Wop Thwop Snort Sigh Grumble
Amplitude Modulated	Combination of harmonic and amplitude modulated components- modulation close to fundamental freq	Growl Purr Trill
Repetitive	Short, low freq sounds in groups	Grunt Croak Yaps, Low Yaps Pulses Gurgle
Noisy/complex	Short, high level sounds with wide freq range (45-10,000 Hz)	Bark Bellow Creak Screech Scream

Mid Frequency	Between low and high freq	Siren Groan Short moan Horn Violin Cry
High Frequency	Sound usually ascending or descending	Shriek Squeak

Table 1: Unit catalog based on the group classifications according to the Dunlop and Fournet papers.

Unit Labels	**Descriptions (± Frequency range (low-high) in Hz)**
Cry	338-709
Modulated moan	201-618
Modulated cry	524-1415
Groan	139-172
Ascending shriek	714-2268
Ascending moan	162-271
Descending shriek	809-1373
Descending moan	Below 700
Gurgle	50-300, upsweep, occur in groups/bouts
Grunt	50 and below, occur in bouts
Purr	56-59

Trill	245-427
Growl	60-73
Bark	139-346
Low Yap	243-820
Violin	548-908
Horn	180-430
Squeak	1431-2420
Siren	95-337
Bellow	382-403
Broadband burst	64-3611
Creek	29-102
Croak	75-120
Grumble	43-48
Pulse	139-294
Scream	678-1436
Screech	119-221
Sigh	30-327

Snort	51-53
Thwop	42-83
Trumpet	231-854
Wop	43-73

Table 2: Distinction of individual unit types with ± average frequency range (Hz) according to the Dunlop paper (Dunlop *et al.,* 2007).

Unit Type	Bark	Bellow	Broadband Burst	Creak	Croak	Cry	Groan	Growl	Grumble	Grunt	Gurgle	Low Yaps	Moan	Pulse	Purr	Scream	Screech	Shriek	Sigh	Siren	Snort	Thwop	Trill	Trumpet	Violin	Wop
1	0	0	0	0	0	6	13	0	0	0	8	0	7	0	0	0	0	1	0	0	0	0	1	0	0	0
2	0	0	0	0	0	18	7	0	0	0	21	0	34	0	4	0	0	1	8	1	0	0	0	0	0	0
3	0	0	1	0	0	0	1	0	0	0	31	0	33	0	0	0	0	4	0	0	0	1	8	0	0	0
4	6	0	16	0	0	14	18	0	0	9	36	0	21	0	7	0	0	11	0	0	0	0	4	1	0	0
5	0	6	0	0	11	0	4	0	1	32	58	0	21	0	8	0	0	35	0	0	1	0	24	0	0	0
6	0	0	0	0	0	0	0	1	0	3	1	0	52	0	0	0	0	4	0	0	0	0	0	0	0	0
7	0	0	0	1	0	3	7	0	2	0	29	4	19	8	7	0	0	13	0	0	0	0	0	0	1	0
8	0	5	0	0	0	0	0	0	0	18	8	0	27	0	0	0	0	11	0	0	0	0	0	0	0	0
9	0	0	0	6	1	13	1	0	0	46	14	0	41	0	11	11	1	40	0	0	0	0	7	0	0	1
10	4	0	0	0	0	28	0	12	0	50	22	5	35	0	0	0	0	0	0	0	0	0	0	0	0	8

Table 3: The number of unit types in each of the 10 songs. The yellow boxes show the most repeated unit type, orange shows the second most repeated unit type, and green shows the third most repeated unit type.

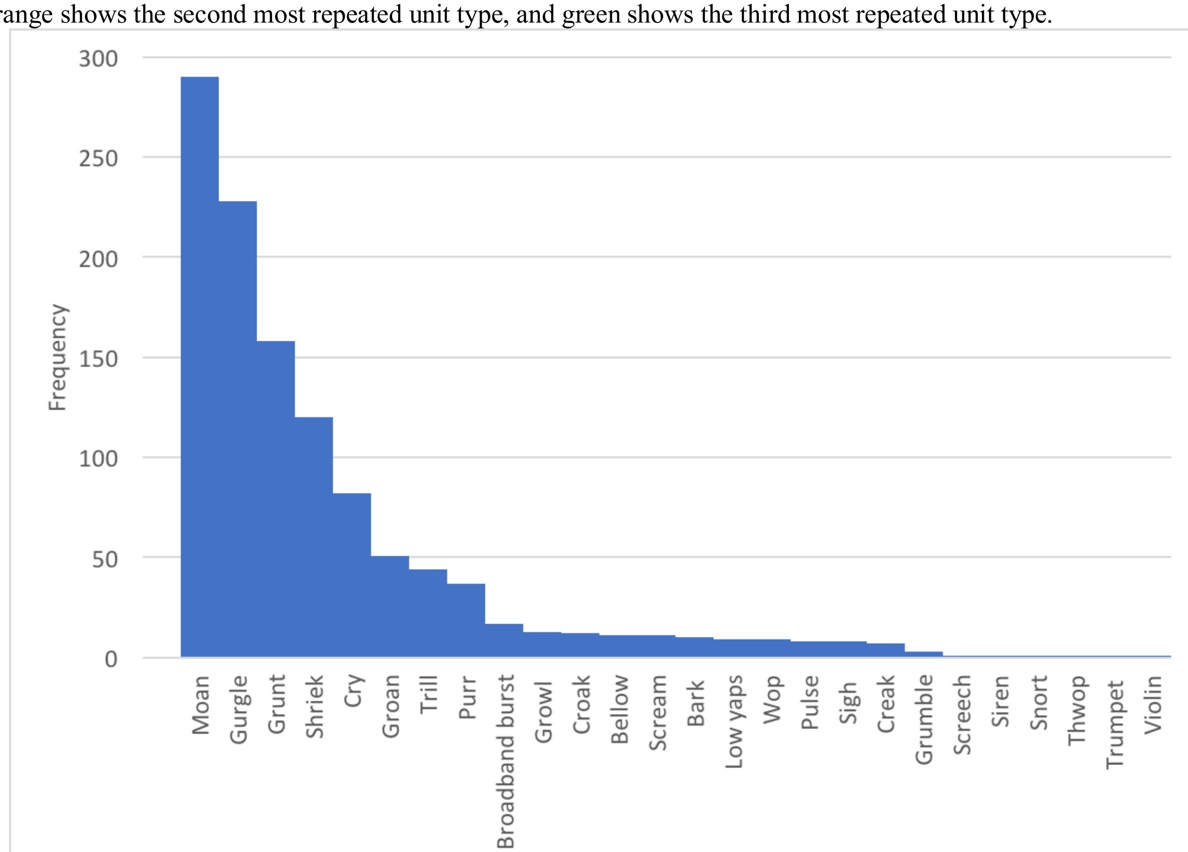

Figure 4: These are the 26 different unit types I identified in the ten songs I analyzed and their frequency (occurrence) among the ten songs.

Song Selection	Number of Unit Types	Unit Types
20151207	11	Bark, Broadband burst, Cry, Groan, Grunt, Gurgle, Moan, Purr, Shriek, Trill, Trumpet
20161207	11	Creak, Cry, Groan, Grumble, Gurgle, Low yaps, Moan, Pulse, Purr, Shriek, Violin
20170107	5	Bellow, Grunt, Gurgle, Moan, Shriek

Table 4: This table shows unit types from year to year.

Song Selection	Number of Unit Types	Unit Types
20151022	6	Cry, Groan, Gurgle, Moan, Shriek, Trill
20151121	7	Broadband burst, Groan, Gurgle, Moan, Shriek, Thwop, Trill
20151228	11	Bellow, Croak, Groan, Grumble, Grunt, Gurgle, Moan, Purr, Shriek, Snort, Trill

Table 5: This table shows unit types from month to month.

Song Selection	Number of Unit Types	Unit Types
20161101	5	Growl, Grunt, Gurgle, Moan, Shriek
20161207	11	Creak, Cry, Groan, Grumble, Gurgle, Low yaps, Moan, Pulse, Purr, Shriek, Violin
20170107	5	Bellow, Grunt, Gurgle, Moan, Shriek

Table 6: This table also shows unit types from month to month.

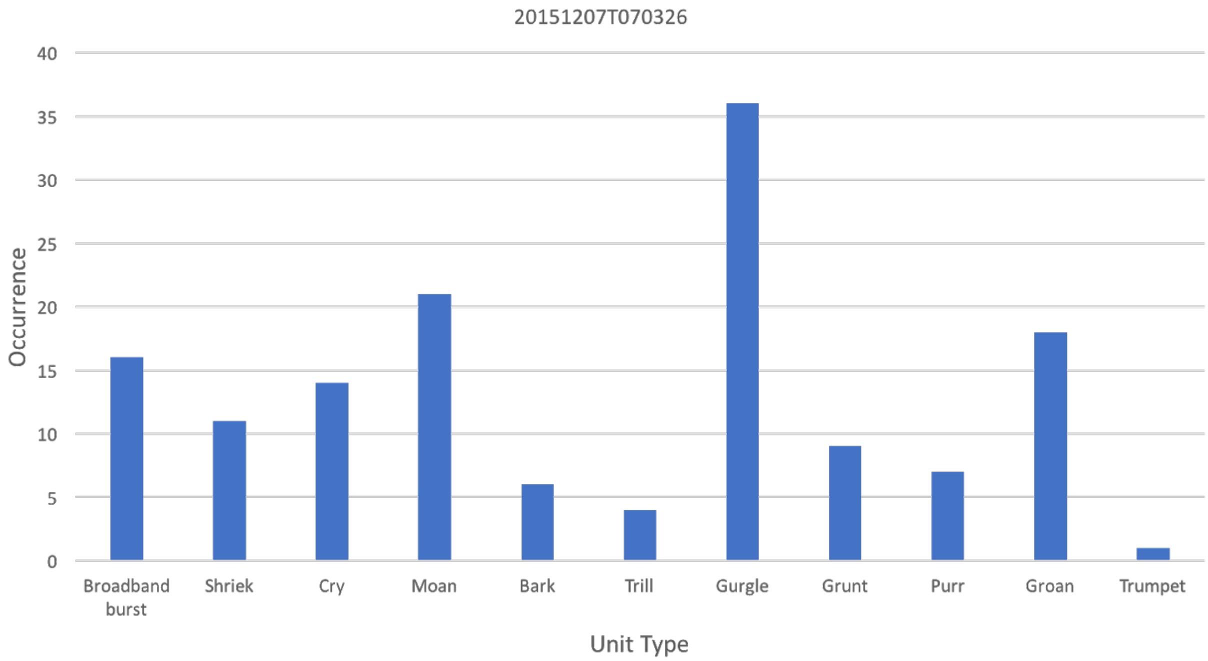

Figure 5: This graph shows the 11 different unit types within this 20151207 song I labeled.

Song Selection	Song Date
1	20151022T015622
2	20151023T122324
3	20151121T040102
4	20151207T070326
5	20151228T103639
6	20161101T153358
7	20161207T115528
8	20170107T085150
9	20170116T054541

10	20170424T102157

Table 7: These are the ten songs that I labeled. Date follows this format: year, month, day, hour, minute, second.

Song	Song Duration (sec)	Avg Duration of Unit (sec)	Total Number of Units	Number of Unit Types	Low Frequency (Hz)	High Frequency (Hz)
1	139	2.04	36	6	56	895
2	398	2.10	94	8	85	1533
3	422	1.90	79	7	123	792
4	394	1.47	143	11	78	1638
5	600	1.25	201	11	52	1773
6	477	4.28	61	5	132	725
7	275	1.44	94	11	54	1819
8	313	1.34	69	5	103	1037
9	613	1.80	193	13	66	1882
10	630	1.70	164	8	55	1923

Table 8: For the ten songs I labeled, I recorded some important measurements in order make conclusions about song patterns and complexity.

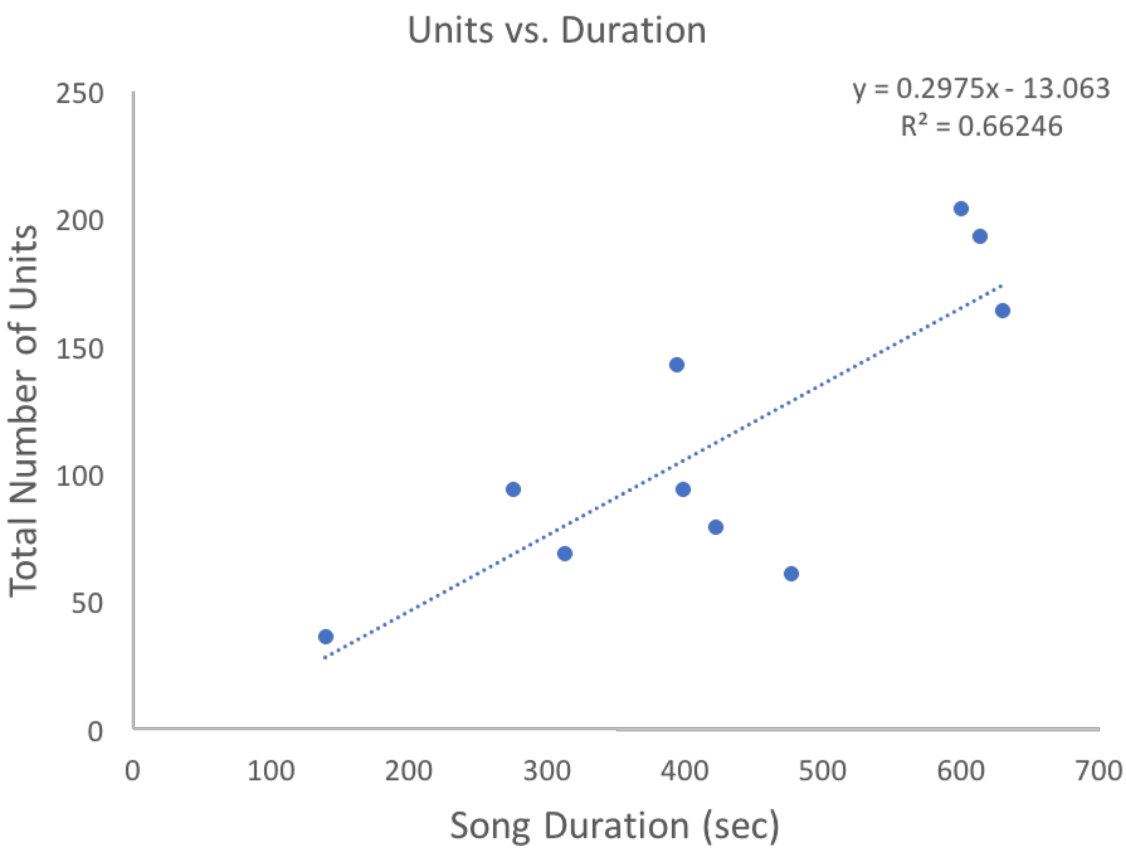

Figure 6: This plot shows song duration for all ten songs versus total number of units within a song.

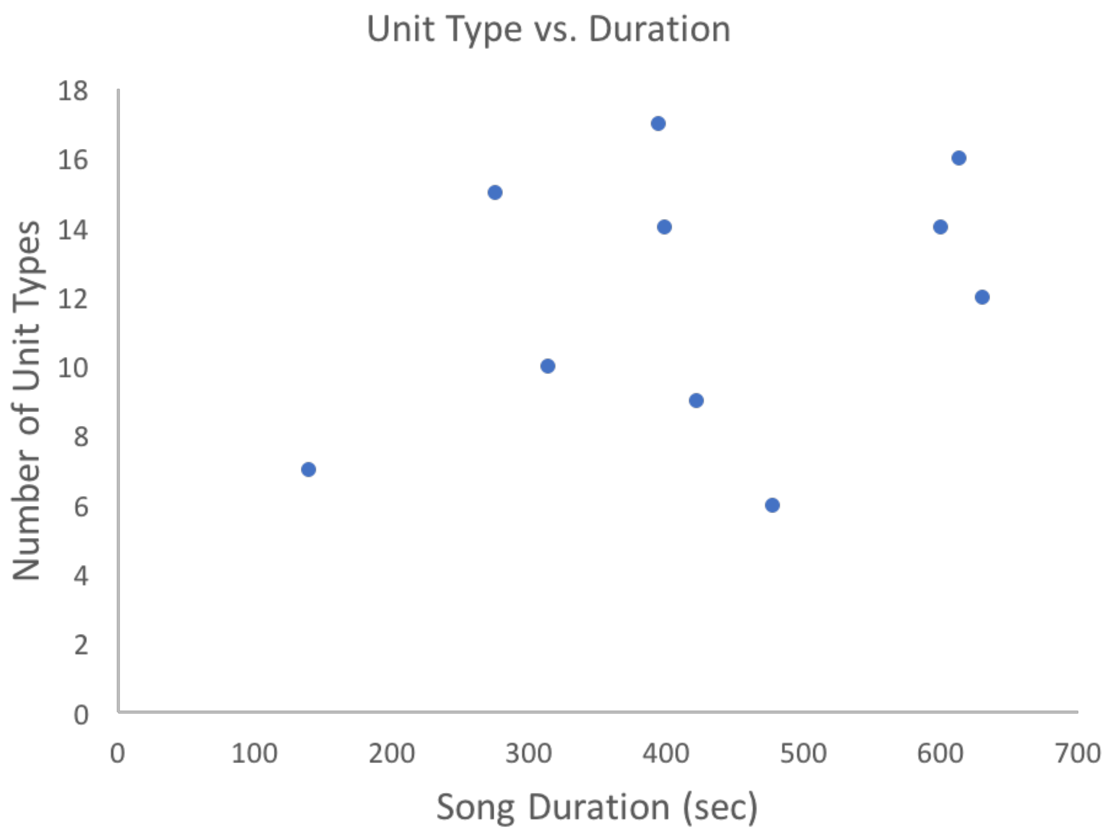

Figure 7: This plot shows song duration versus number of unit types within each of the 10 songs.

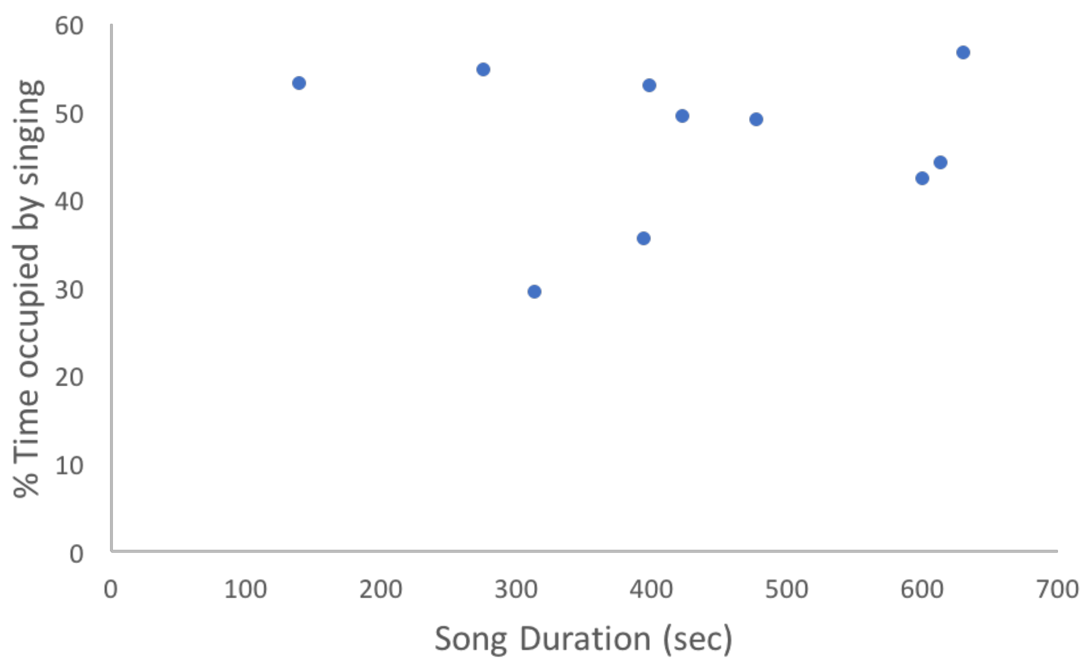

Figure 8: This plot shows song duration versus percent time the song was occupied by singing.

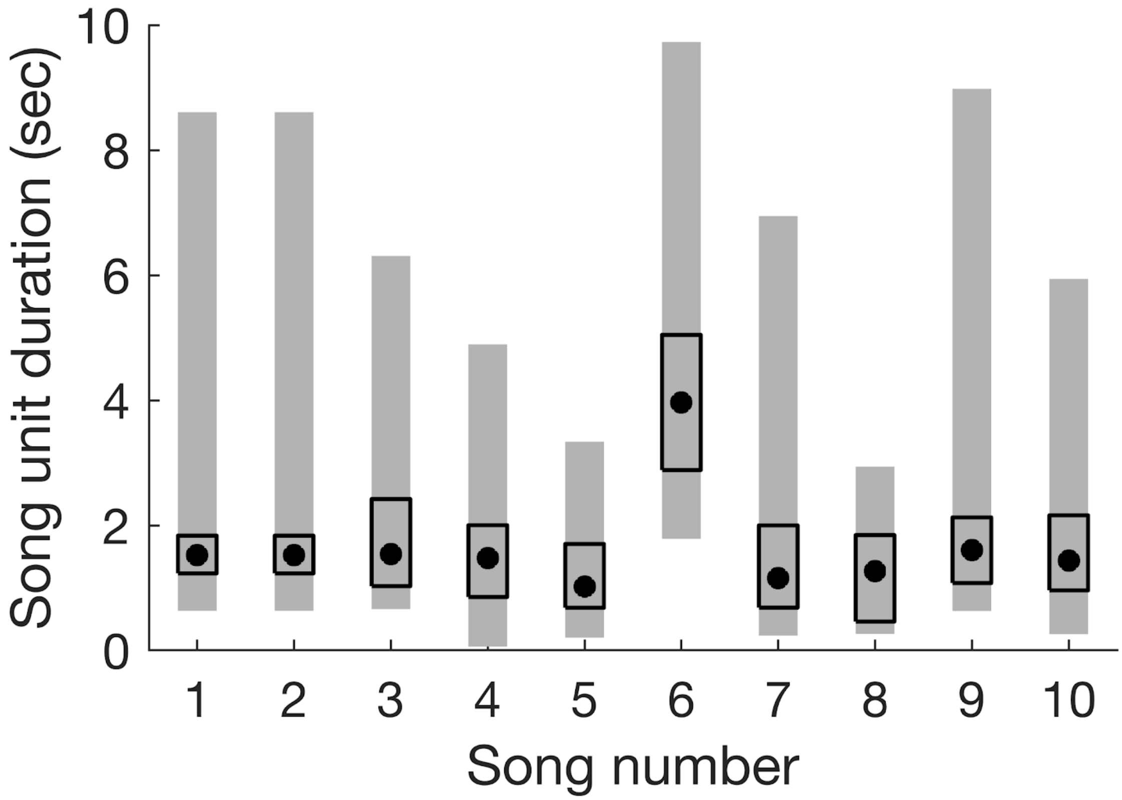

Figure 9: In this nonparametric box plot, the grey bars represent the song unit duration range, while the boxes represent the first (25%) and third (75%) quartiles and the dot represents the median song unit duration (Ryan).

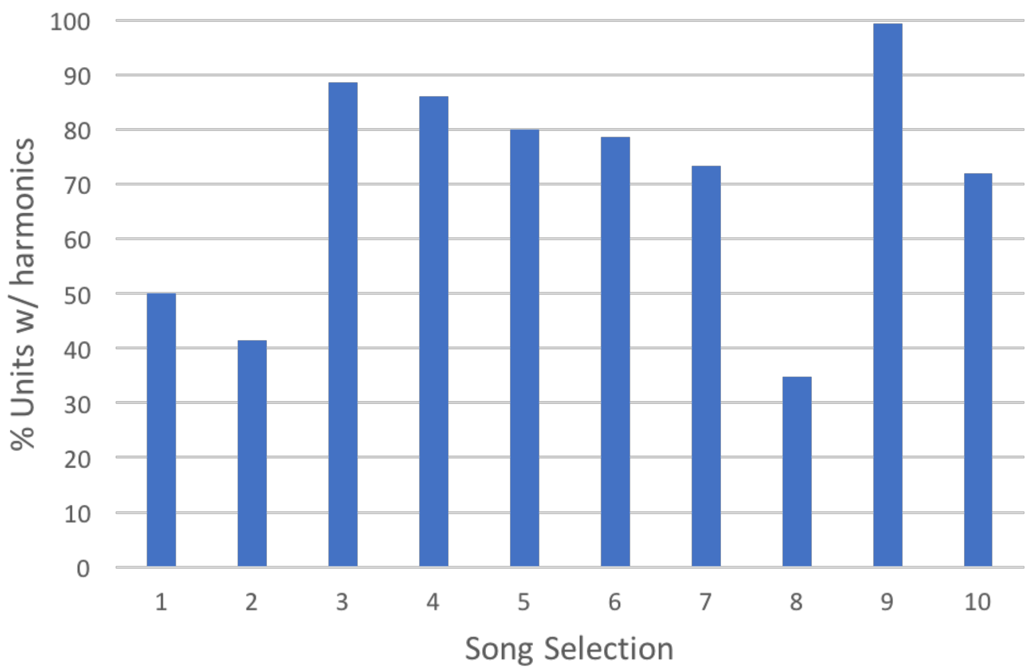

Figure 10: This bar graph shows each song and the percentage of units that contain harmonics.

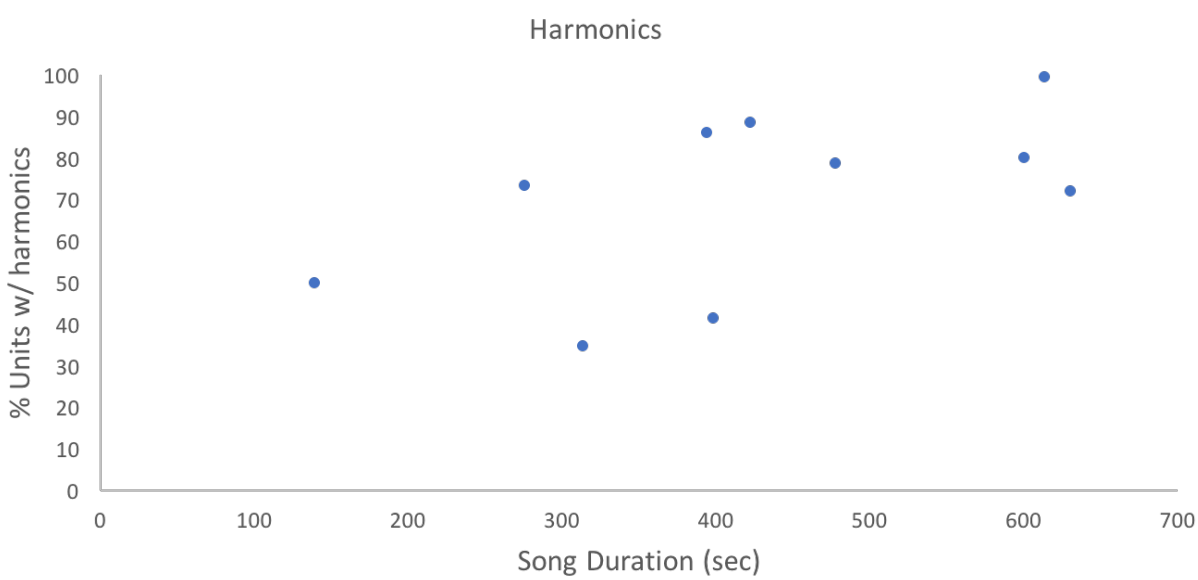

Figure 11: This plot shows song duration versus percentage units containing harmonics.

DISCUSSION

Results show that the most popular unit type was the moan, followed by gurgle, grunt, shriek, cry, groan etc. (Figure 4). In the 20151207 song, even though gurgle was the most popular unit type, it only made up about 24% of the song, further proving the complexity within one song (Figure 5). This song became my favorite as it had a high signal to noise ratio. Furthermore, the results helped us answer some questions about the evolution of humpback song and patterns. From 2015 to 2016, there was an overlap of six unit types: cry, groan, gurgle, moan, purr, and shriek (Table 4). From 2016 to 2017, there was an overlap of three unit types: gurgle, moan, and shriek (Table 4). Then from October to December of 2015, we saw an overlap of five unit types: groan, gurgle, moan, shriek, and trill (Table 5). From November to January 2016, there was an overlap of three unit types: gurgle, moan, and shriek (Table 6). Across all patterns with an overlap of units, it became apparent that all possess the gurgle, moan, and shriek units. To note, in table 8 the high frequency upper bound decided upon was 2,000 Hz. Units containing harmonics extend beyond 24,000 Hz but for our analyses, a frequency range of 50-2,000 Hz was chosen. Song duration was compared to several variables to observe patterns within song structure. An increase in song duration did correlate with an increase in total number of units but did not correlate with an increase in complexity of the song, or increase in number of unit types (Figure 6, 7). Song duration did not relate to a greater or lesser percentage of time the whales spent singing (Figure 8). Even with a longer song, whales weren't necessarily taking more pauses or breaks between units. As my data did not follow a normal distribution, I chose a nonparametric box plot to represent song unit durations (Figure 9). Song unit duration medians seemed to remain fairly constant despite the wide song unit duration range. There seemed to be an outlier at song number 6 but that could be justified by a couple units with a longer duration. The majority of songs contained units with harmonics and units containing harmonics included the groan, moan, cry, purr, bellow, grunt, and trill (Figure 10). As song length increases, percentage of units containing harmonics did not necessarily increase (Figure 11).

Anytime you incorporate a human comes a degree of subjectivity, especially in the labeling of units. Observers examine vocalizations based on different criteria. Oftentimes it was between 2 units when labeling, sometimes more, and I had to decide which one was the closest to the spectrograms and tables according to the literature. Also, I sometimes relied on the sound of the unit from the spectrogram but I tried not to rely on that method.

CONCLUSIONS/RECOMMENDATIONS

Humpback songs consist of a complex structure, which we can only make preliminary conclusions. Units span a wide frequency range but for our analysis we focused on the 50-2,000

Hz frequency range. They include upsweeps, downsweeps, tones, and pulses. Song selection was based on whether it had a high signal to noise ratio or ease with which to distinguish signal relative to background noise. My exploration of humpback song structure from MARS' recordings followed the traditional method, forming the "ground truth" for machine learning methods. From the 10 songs I labeled, I identified 26 distinct unit types. I discovered that the majority of songs incorporate harmonics. While song unit duration varies greatly, median song unit duration within each song ranges between 1-2 seconds. According to further inspection of the songs, it can be inferred that total song duration correlates positively with the total number of units but does not correlate with an increase in song complexity, increase in percentage of units containing harmonics, and an increase or decrease in time spent singing.

By taking the traditional method approach for labeling song units, I discovered that when comparing units from the songs I analyzed with literature classification of units, reference to audio files allowed me to further validate my classification. While we were able to determine some of the changes of the song repertoire over time, exploration of patterns and evolution of song needs to be conducted with a larger data set. The traditional method proves remarkably time consuming and tedious; therefore, the need to replace a human with machine learning. Machine learning certainly could assist in removing the subjectivity in the distinction between unit types. In other words, a standard vocabulary could be the result of the ROST model, establishing a common catalog of song units. While future work for Tom includes determining a way for the topic modeling results to show a distinction between different types of units, his results did demonstrate a differentiation between signal (units) and noise. To truly understand the function of these songs would require further analysis on the behavior of humpback whales alongside their vocalizations.

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