Earth Science Project:
Passive Acoustic Monitoring

Andrew Bartels, Gabe Shindnes, Jeff Louie, Hunter Clark, Jessie Gorges

Introduction:
The oceans depths are a vast, largely unexplored, resource. Passive Acoustic Monitoring (PAMS) provides a long term view into a location using sound. Deepening our understanding, of both the ecosystem and our interactions with it will help preserve its resources by allowing us to protect endangered species, make better policy decisions and reduce our impacts. Our goal was to see if we could improve on current methods of PAM analysis, by making the process faster, more user friendly and enable more automation by classifying sound features automatically instead of by hand going from sample to sample.

Stage 1

Pull Raw Data

Pull raw acoustic data from NOAA, and AIS (boat location) data from Marinetraffic.com

PAMS Data:
2.7 TB of raw audio was downloaded from NOAA Ocean and Atmospheric Research group (OARs).

AIS Data
1 TB of AIS (Automatic Identification System) shipping data was downloaded directly from the NOAA AIS handler

Classification Data:
13.24 GB of raw audio was obtained from a teammate and downloaded from voicesinthesea.ucsd.edu

Filter & Process

Using python process raw acoustic into features automatically and format AIS data import into django with a sqlite backend

Stage 2

Final:	PAMs	AIS	Classification
Size on Disk	157 GB	4.5GB	1400 MB
# of Records	256,691	60,000,000	614
# of Features	26	6	26,000
Temporal	2018	2018-2021	NA
Filtered	Yes	Yes	Yes

PAM Sound Processing:
The initial 2.7 terabytes of sound data was converted from .flac to .wav using the python scikit-maad package. The background noise was removed using median_equalizer and converted power to decibels (dB).
The spectrogram was smoothed using 2 std deviation Gaussian filter to remove more background noise along the vertical axis.
A binary mask was created from the smoothed image and regions of interest were selected filtering on min, max and size of area.
The selected regions were cropped, a 9 second clip with the sound in the center was saved and the features were pushed into a database.

AIS Processing:
AIS was filtered keeping only boats that passed within 100km of the PAMs buoys, and had more than 5 plotted points. The only features kept were MMSI (unique boat IDs), DateTime of location, latitude, longitude, and vessel type. Vessel type was used to generate a column for the class of each boat.

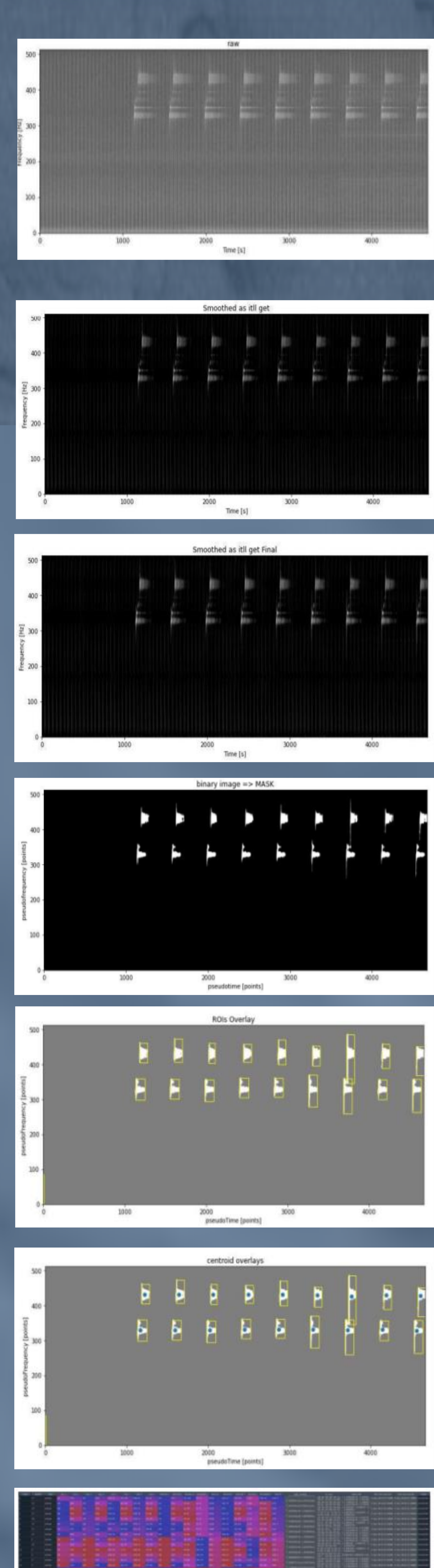
Classification Processing:
All audio samples were down sampled to 8kHz and were clipped into 5 second chunks to provide a consistent vector length. Samples were then fed in to a mel-frequencey cepstral coefficients(MFCC) filter .

Stage 3

Classify and Analyze

Using machine learning an D3, label and display data to the front end

Manually sampled data from the PAMs results were combined with the classification data and both were run through a 7-layer deep neural network model that differentiated between non-linear irregularities that exist between animals sounds, and human-made noise (I.e. boats, oil-rigs, etc.)

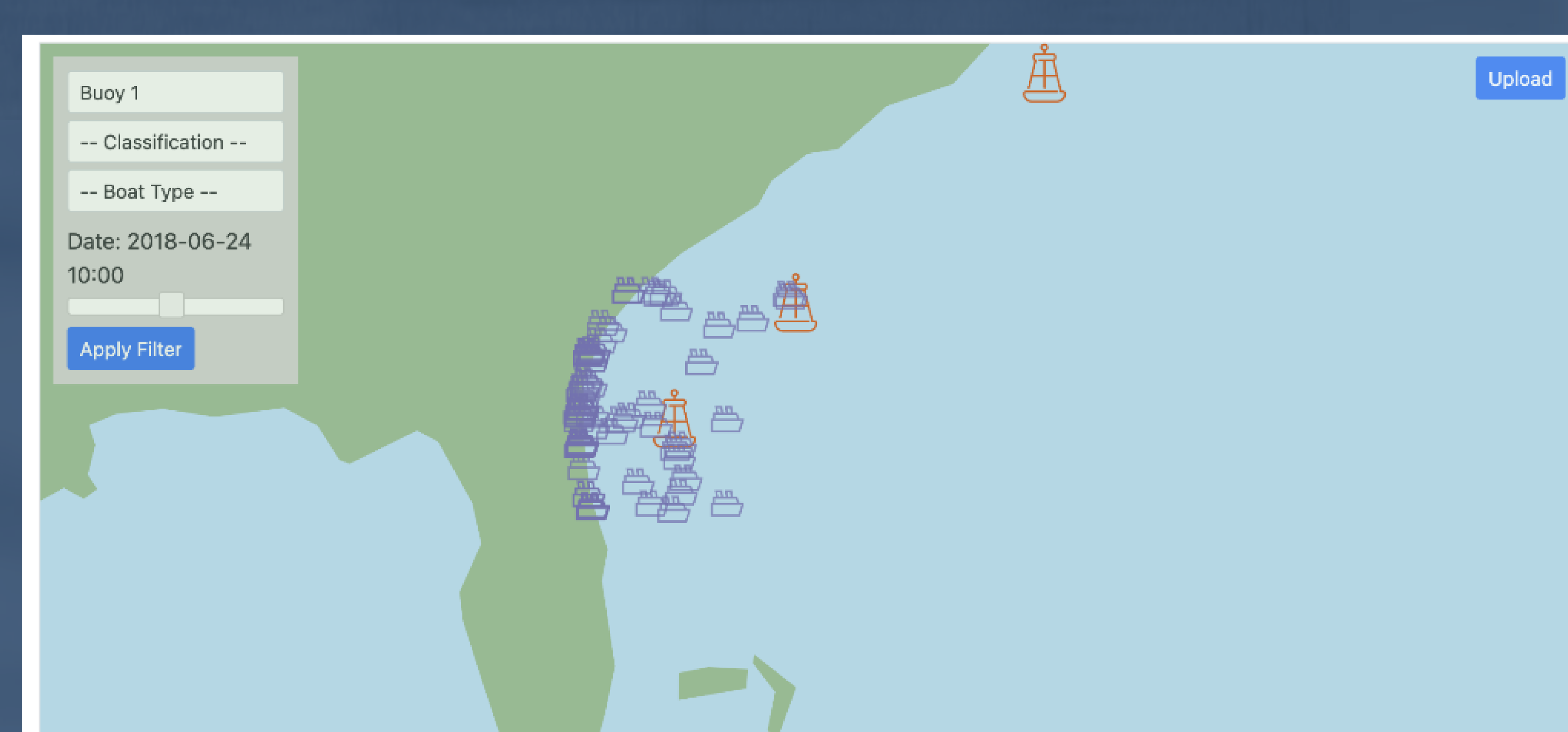


View and Assess

View and Assess all the data found, users can upload their own clips for classification by the ML algorithm and observe interesting oceanic sounds

Stage 4

All this data was funneled into a web app that allows users the opportunity to listen to sound clips based on a chosen time and view the nearby boats. Additionally, they can upload their own clips to see which species their sound most closely resembles utilizing our machine learning sound classification model.



Technologies used	
PAMS Processing	Scikit-maad, Django, Pandas, SQLite
AIS processing	Pandas, SQLite
Sound Classification	python, NumPy, SciPy, Keras, scikit-learn, Pandas, wavfile, wave
Backend	Django, Docker, SqLite
Front End	JQuery, jquery-ui, D3, Bootstrap (css framework), wavesurfer.js

Results:
We did succeed in increasing speed for processing methods, our system can get through 4-5000 samples per hour, other systems that compute similar things have huge teams of supporters to facilitate data analysis. Additionally, we were able to pick out sounds from ambient ocean noise, including Orcas, seagulls, boats, and sonar and classify them with 65-70% accuracy.
Our approach of combining filtering, classification and AIS data is a novel one, and is a powerful tool for sorting through exhaustive amounts of audio to find features of interest; and will only get better the more it is used. The more samples are provided to the neural network the more accurate it will become and the better it will get at finding features. These tools combined could allow boats to hear nearby animals and avoid them, researchers to better track endangered populations, authorities to pick out suspicious boat activity, and do allow the general public the opportunity to discover and listen to the hidden ocean.