Cornell University

K. Lisa Yang Center for Conservation Bioacoustics

Identifying Individual Right Whales through Passive Acoustic Upcall Recordings

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CornellLab

Individual identification of North Atlantic right whales through passive acoustics would enable streamlined **abundance estimation**.

In prior studies, upcall vocalizations were shown to contain information on both **individual identity** and **age class**.

But this task was approached with **manual features**, and has not yet been addressed with automated **machine learning** techniques.

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ENDANGERED SPECIES RESEARCH
Endang Species Res

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Calls of North Atlantic right whales *Eubalaena glacialis* contain information on individual identity and age class

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Table 4. Classification results of discriminant function analysis for North Atlantic right whale *Eubalaena glacialis* individual and age class based on measurements of upcalls

Grouping	No. of whales	No. of calls	Adjusted chance classification	% correctly classified	Cross-validated % correctly classified
Individual	14	212	22.25	76.9	72.6
Age					
Adult	9	157			
Juveniles	4	45			
Total	13	202	65.37	87.6	86.1

Some Key Challenges…

Dataset Construction: how to evaluate individual identification in passive acoustic monitoring data?

Sample Size Limitation: how to leverage deep learning with small datasets?

Ambient Noise: how to ensure that classifiers are learning characteristics of upcalls, not of noise?

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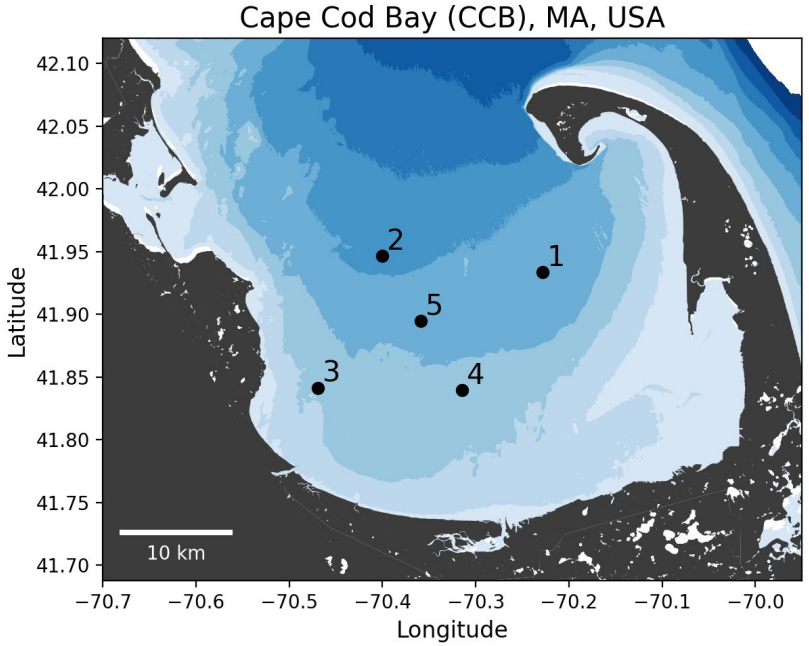


Focal upcall recordings were collected with non-invasive suction cup archival acoustic tags. This work uses 180 total upcalls across 9 individuals.

Image: WHOI

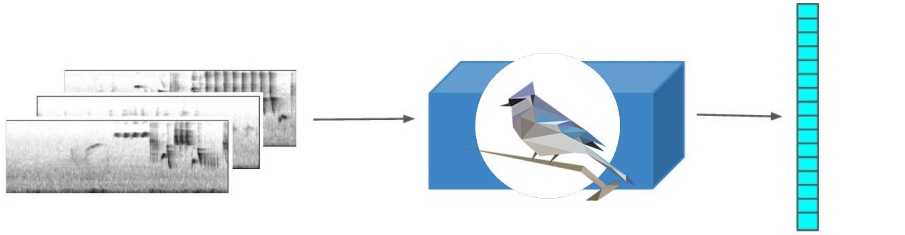
Passive acoustic monitoring data was collected with a bottom-moored five-hydrophone array in Cape Cod Bay between February and June of 2019.

Through a manual examination, it was possible to distinguish individual right whales **calling simultaneously across different channels**.

Some Key Challenges…

Sample Size Limitation: how to leverage deep learning with small datasets?

This challenge can be addressed through **transfer learning.** Specifically, we use the **BirdNET** model.



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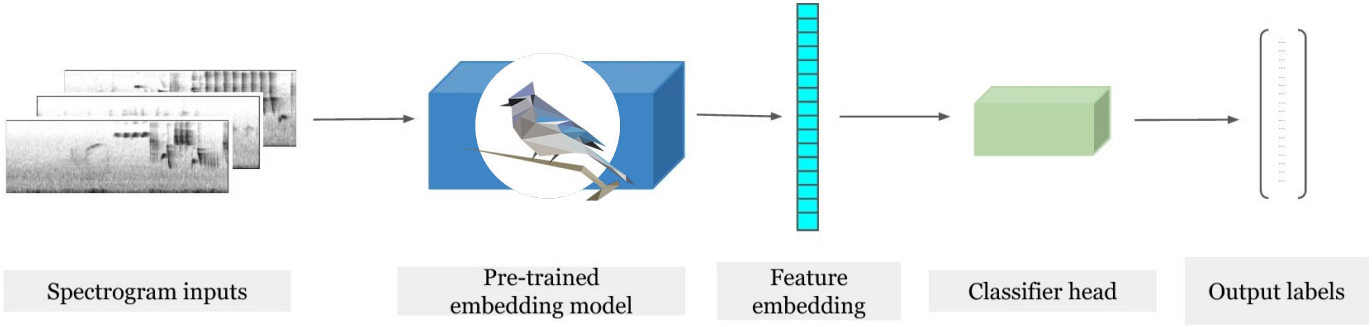

Despite being trained on birdsong, feature embeddings from BirdNET have been **successfully used to classify calls of other taxonomic groups**: including marine mammals, bats, and frogs.

Ghani, Burooj, Tom Denton, Stefan Kahl, and Holger Klinck. "Global birdsong embeddings enable superior transfer learning for bioacoustic classification." Scientific Reports (2023).

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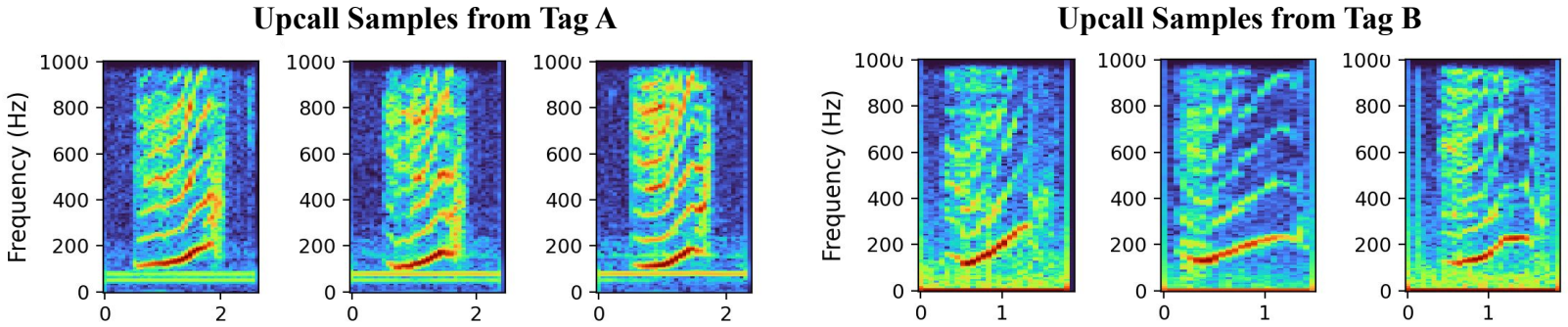
Ambient Noise: how to ensure that classifiers are learning characteristics of upcall, not of noise?



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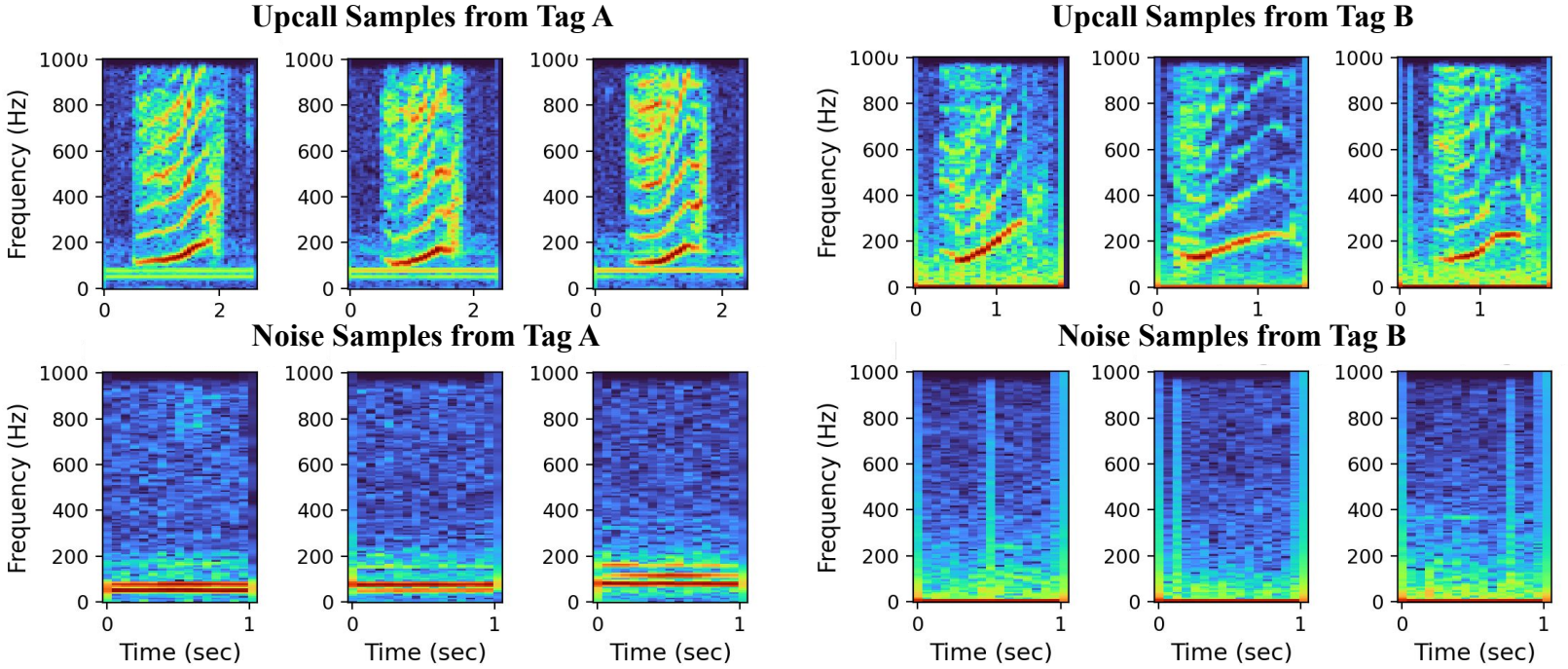

To address this challenge, we apply **rigorous de-noising** and perform **parallel analysis** of ambient noise samples.

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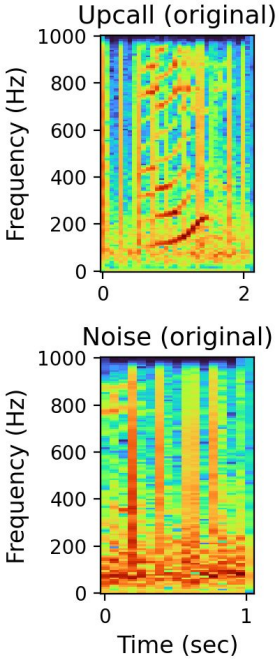

Specifically, we subtract the **time-averaged ambient noise spectrum**, subtract **mean spectrogram row and column values** to mitigate impulsive or narrowband noise, and then **threshold** time-frequency bins below a certain threshold to 0.

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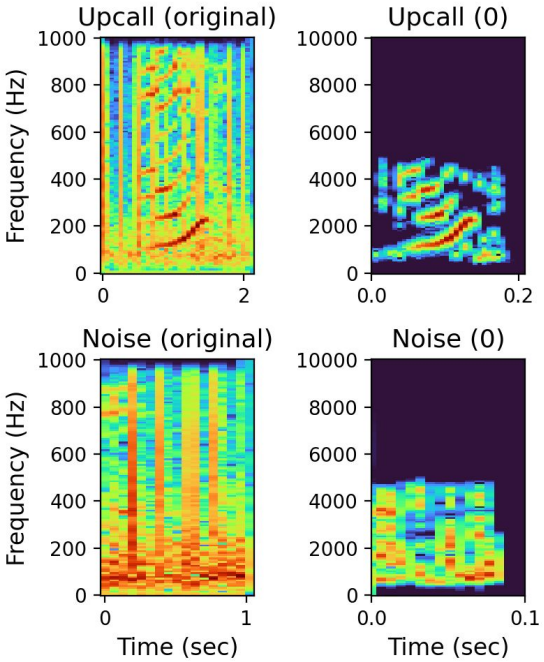

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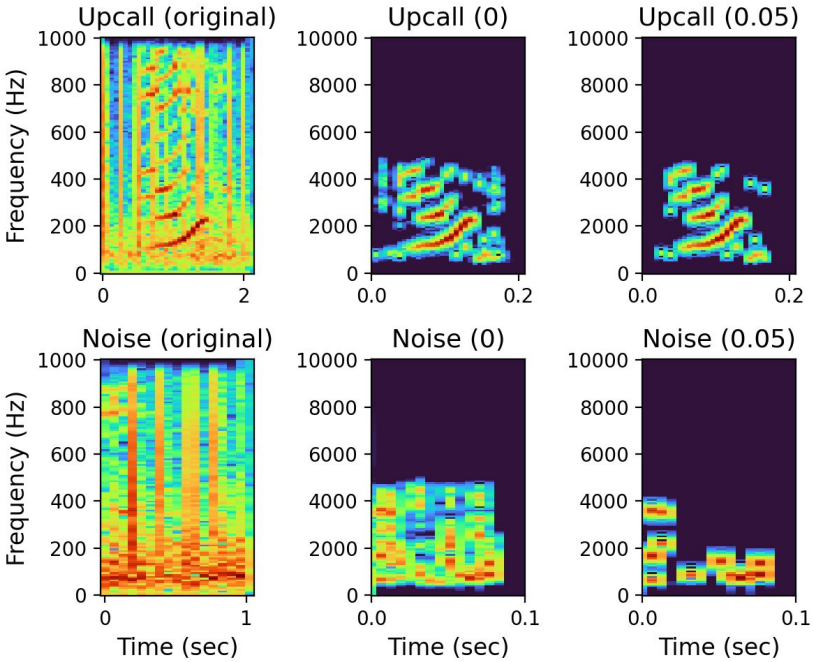

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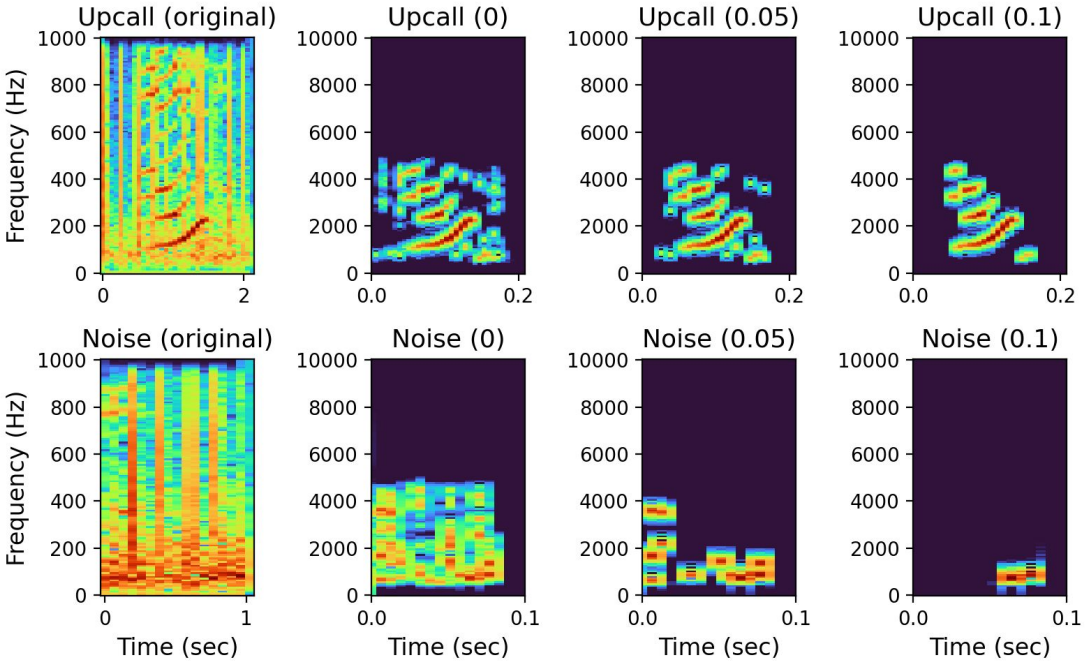

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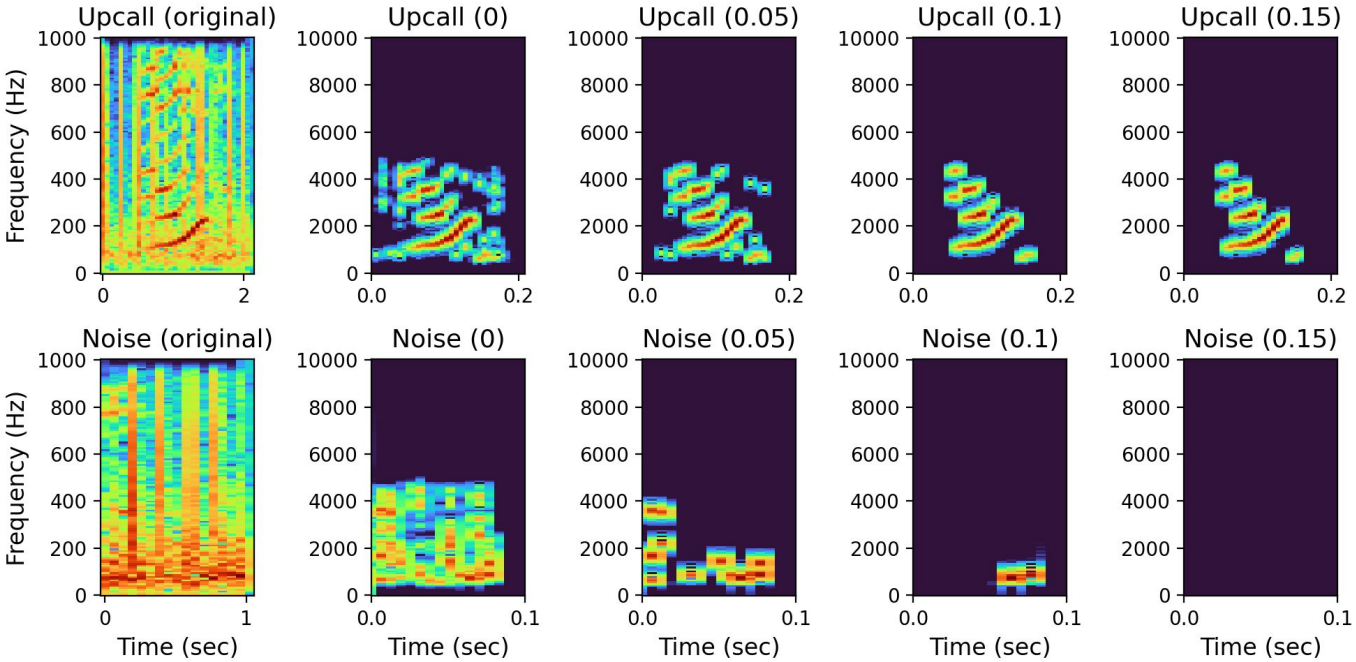

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Results: Tag Data

upcalls and noise samples from **animal-borne tag recordings**

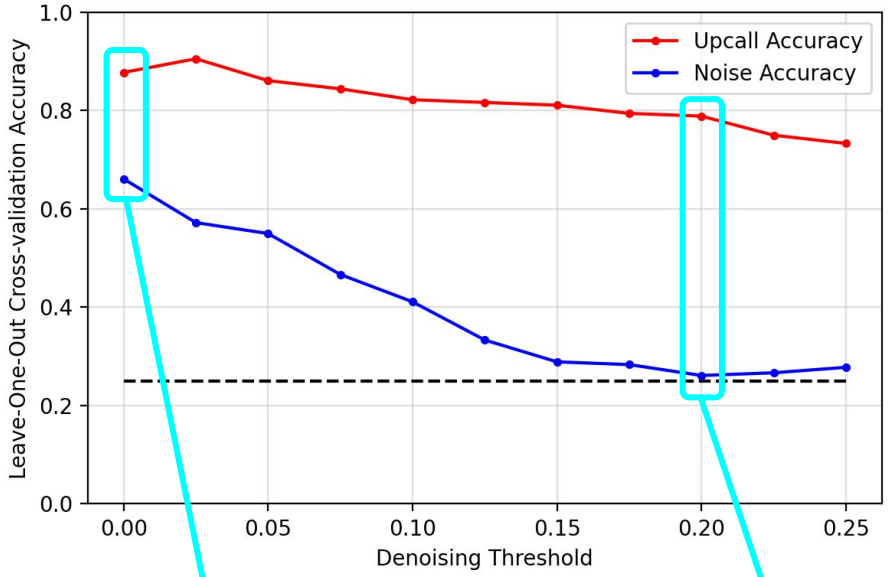
denoising (time-averaged and frequency-averaged spectral subtraction, thresholding) & **upsampling**

BirdNET embeddings (feature vector of size 1024)

evaluate **leave-one-out cross-validation** accuracy on both upcalls and noise samples

dimensionality reduction and visualization with **UMAP**

Classification accuracy across thresholds:



After de-noising without thresholding, we have an upcall accuracy of **88%** and noise classification accuracy of **66%**.

At a threshold of **0.2**, we observe accuracy of **79%** on upcalls, and near-random performance on noise with an accuracy of **26%**.

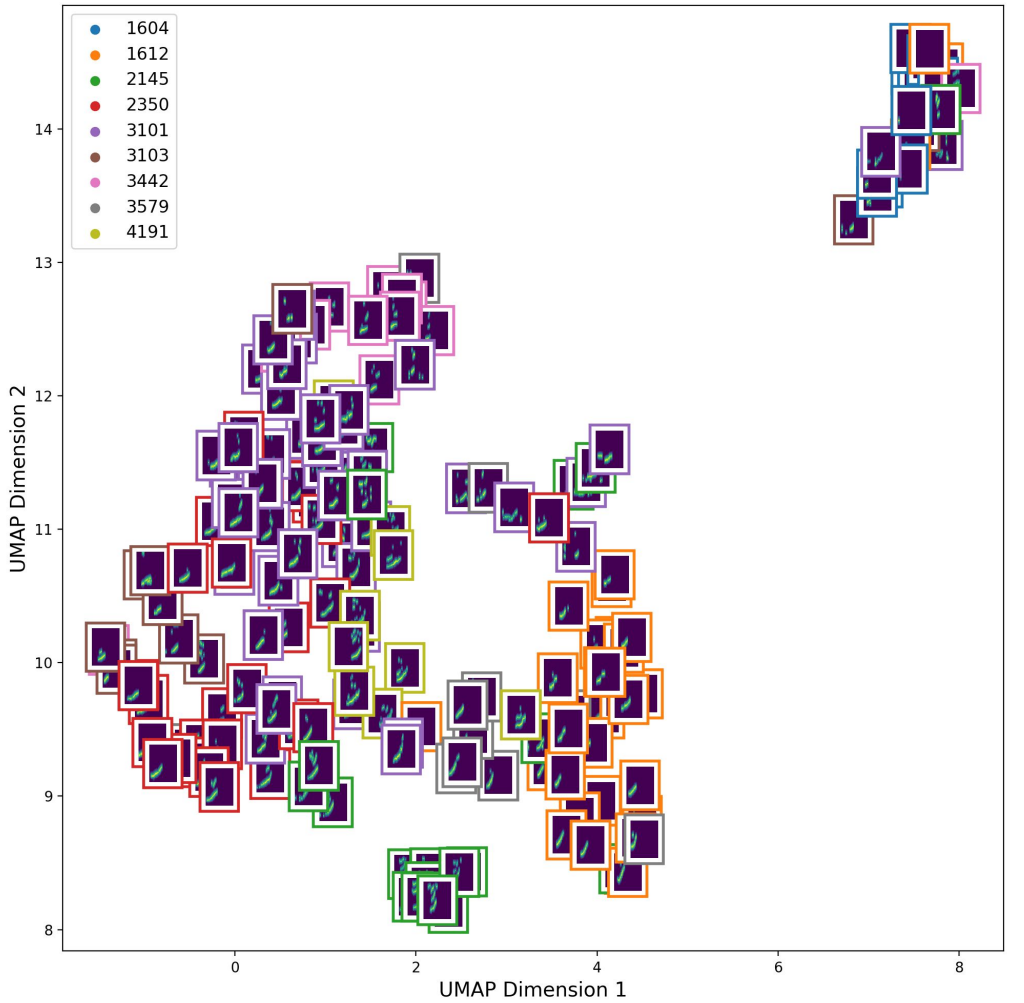
Results: Tag Data

To **visualize lower-dimensional structure**, we further reduce feature dimensionality from 1024 to 2 with **UMAP**, and display all upcalls.

We find that the upcall samples do **cluster by individual**, after accounting for the effects of tag-specific noise.

Altogether, we find that:

- Denoising can successfully mitigate the confounding effect of **tag-specific noise**.
- **BirdNET embeddings** can meaningfully distinguish individual identity within focal upcalls.
- Individual identity is a significant **driver of variability** in upcall structure.



Can we apply this same analysis to passive acoustic recordings?

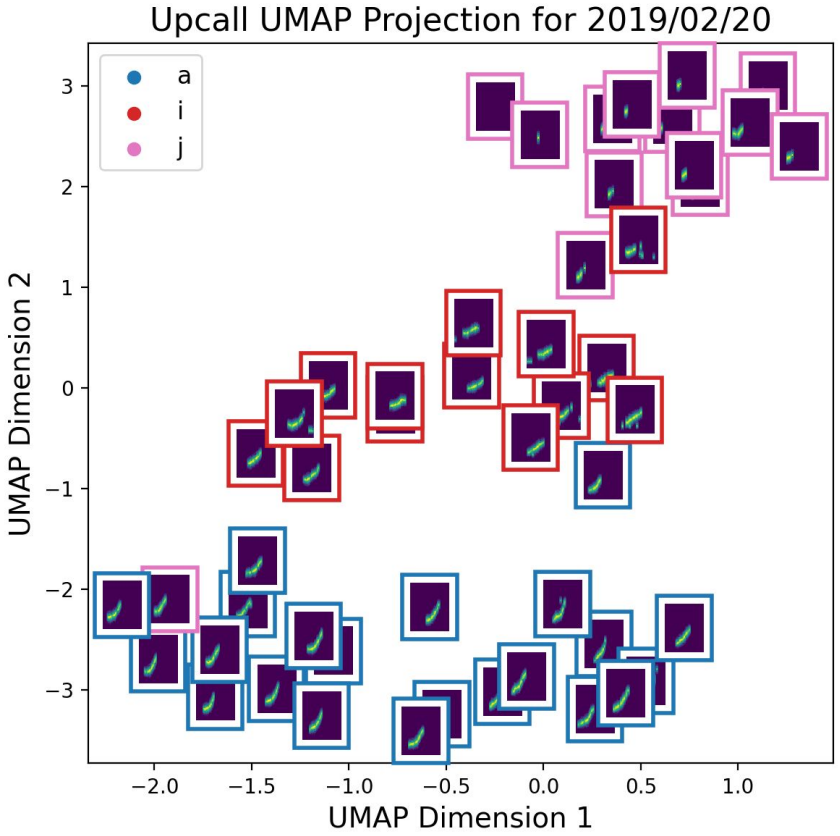
upcalls and noise samples from **passive acoustic recordings** → **denoising & pre-processing** →  → **BirdNET embeddings** → evaluate **leave-one-out cross-validation** accuracies

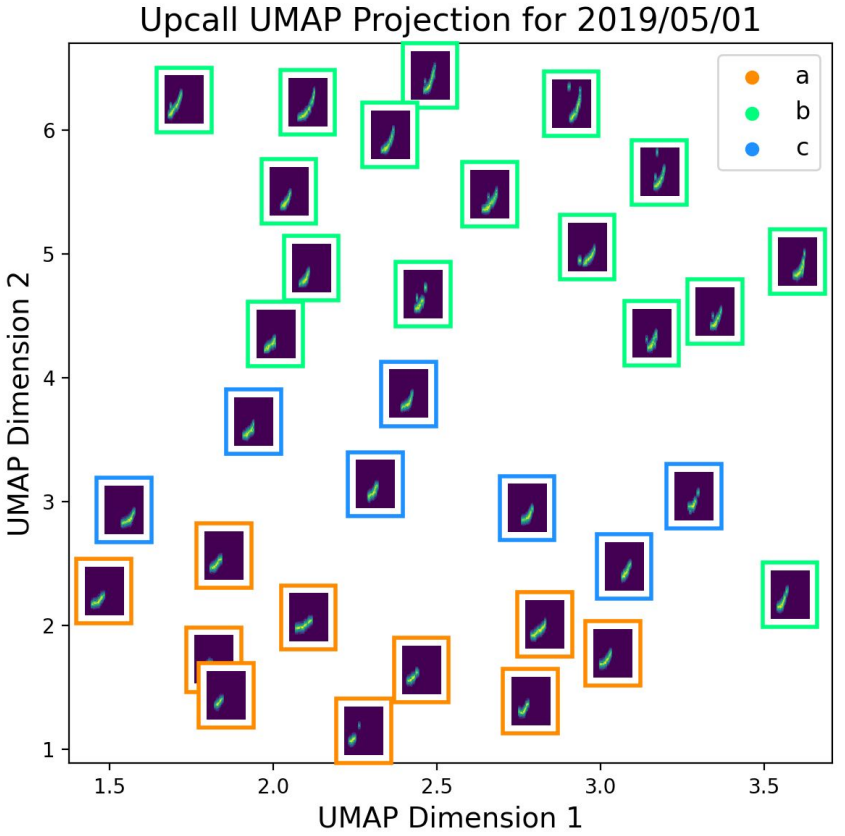
Day	2 / 20	2 / 22	4 / 19	5 / 01
Individuals	3	2	2	3
Total Calls	50	33	34	33
Upcall Accuracy	96%	96%	91%	87%
Noise Accuracy	44%	75%	61%	48%
Random Accuracy	44%	51%	64%	48%

We find that across the different sub-datasets, the BirdNET embeddings allow to **distinguish upcalls with high accuracy**, while obtaining near-random noise classification accuracy.

What does an **unsupervised (UMAP) projection** of the embeddings look like?

Can we apply this same analysis to passive acoustic recordings?

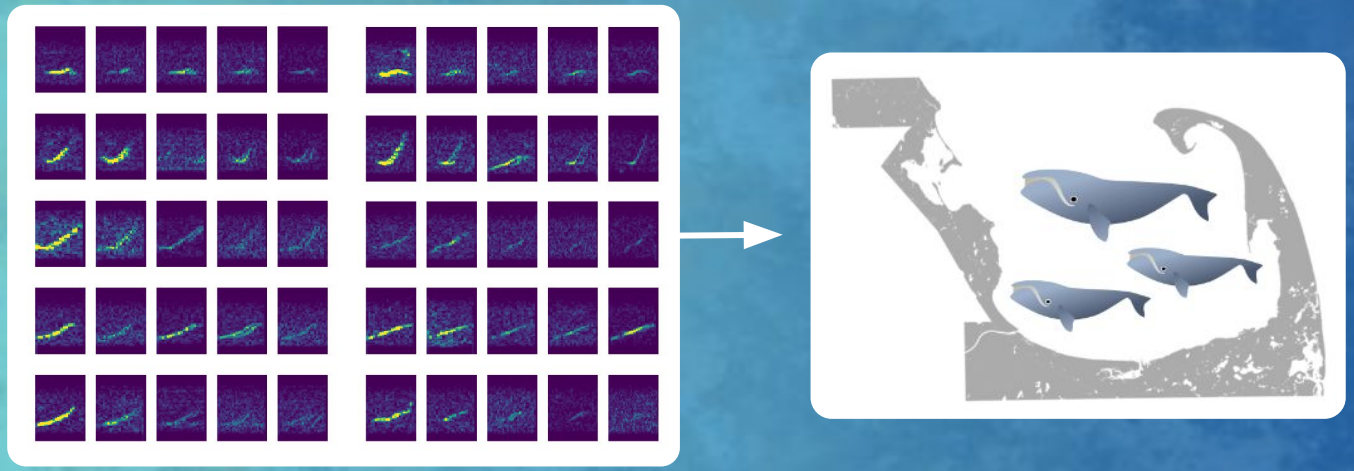




In conclusion…

Feature embeddings can be used to distinguish **individual identity** in **NARW upcalls**, within both **focal and PAM recordings**. In both, individual identity is a significant driver of **variability in vocalization structure.**

Future work: Can we apply this analysis to passive acoustic data to estimate abundance?



Thank you all for listening!

Thank you to my co-authors Holger Klinck, Dana A. Cusano, Anke Kügler, and Susan E. Parks.

Questions?

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