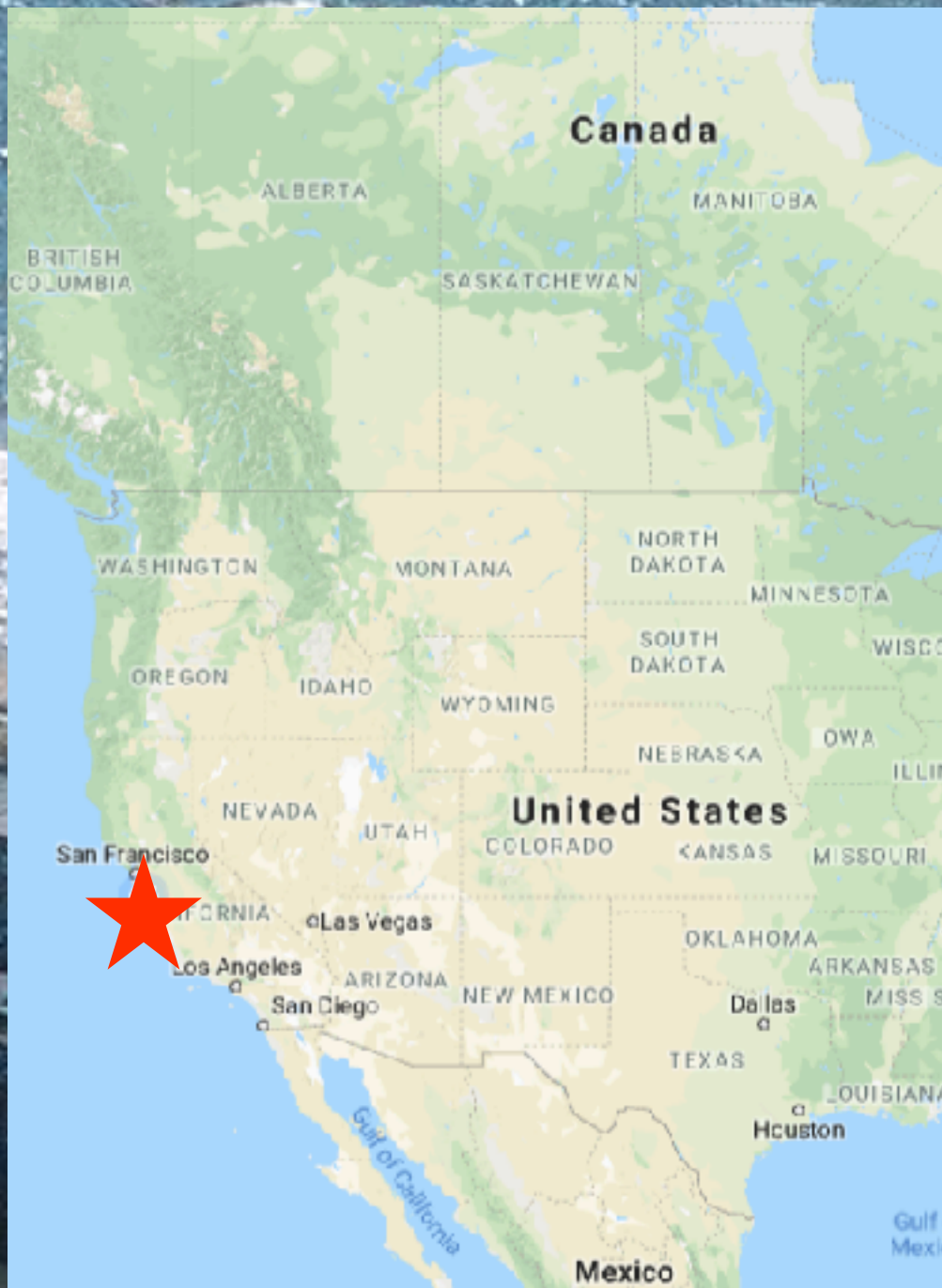


DANELLE CLINE

Detection and classification of whales calls using band-limited energy detection and transfer learning



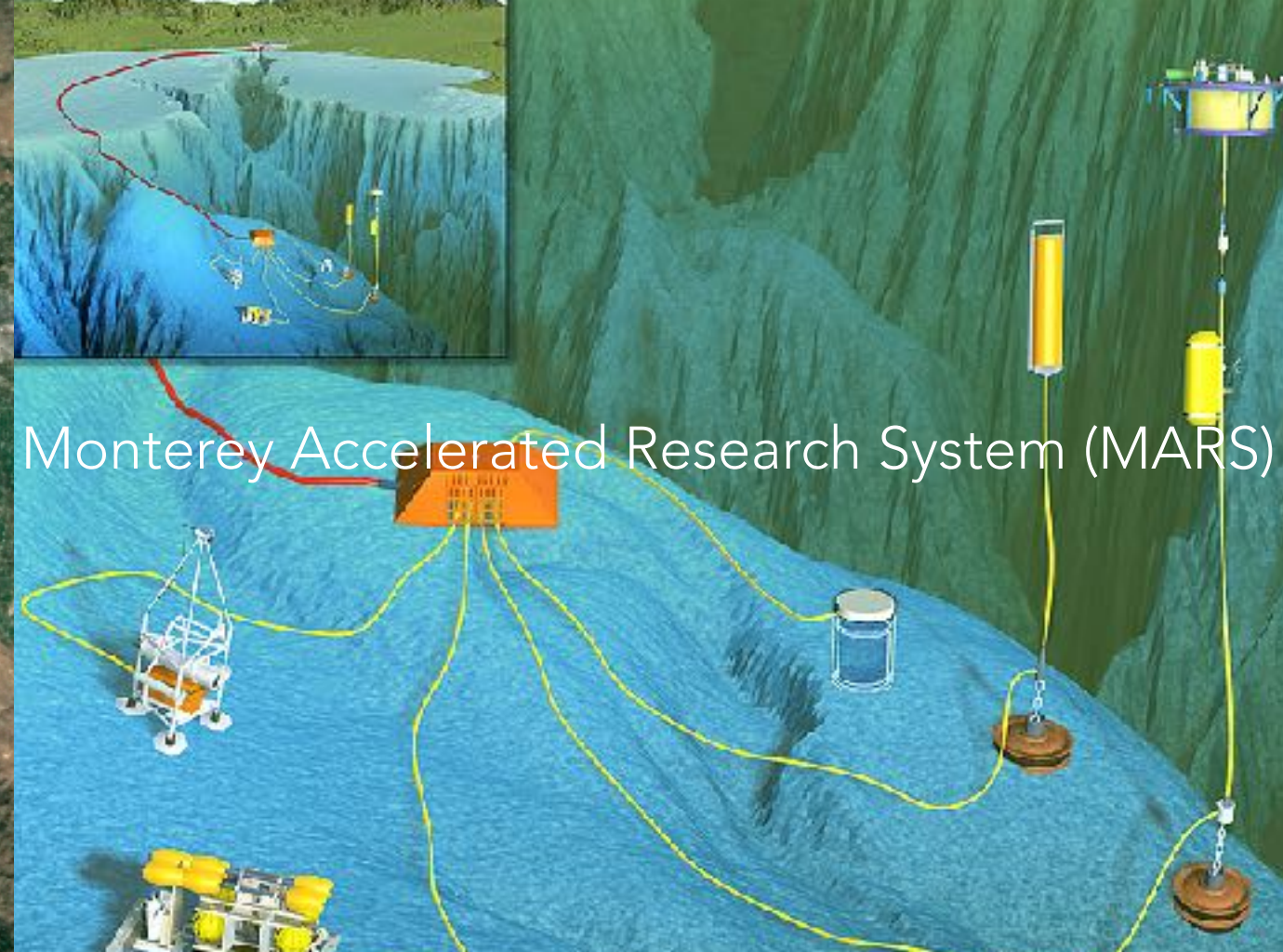
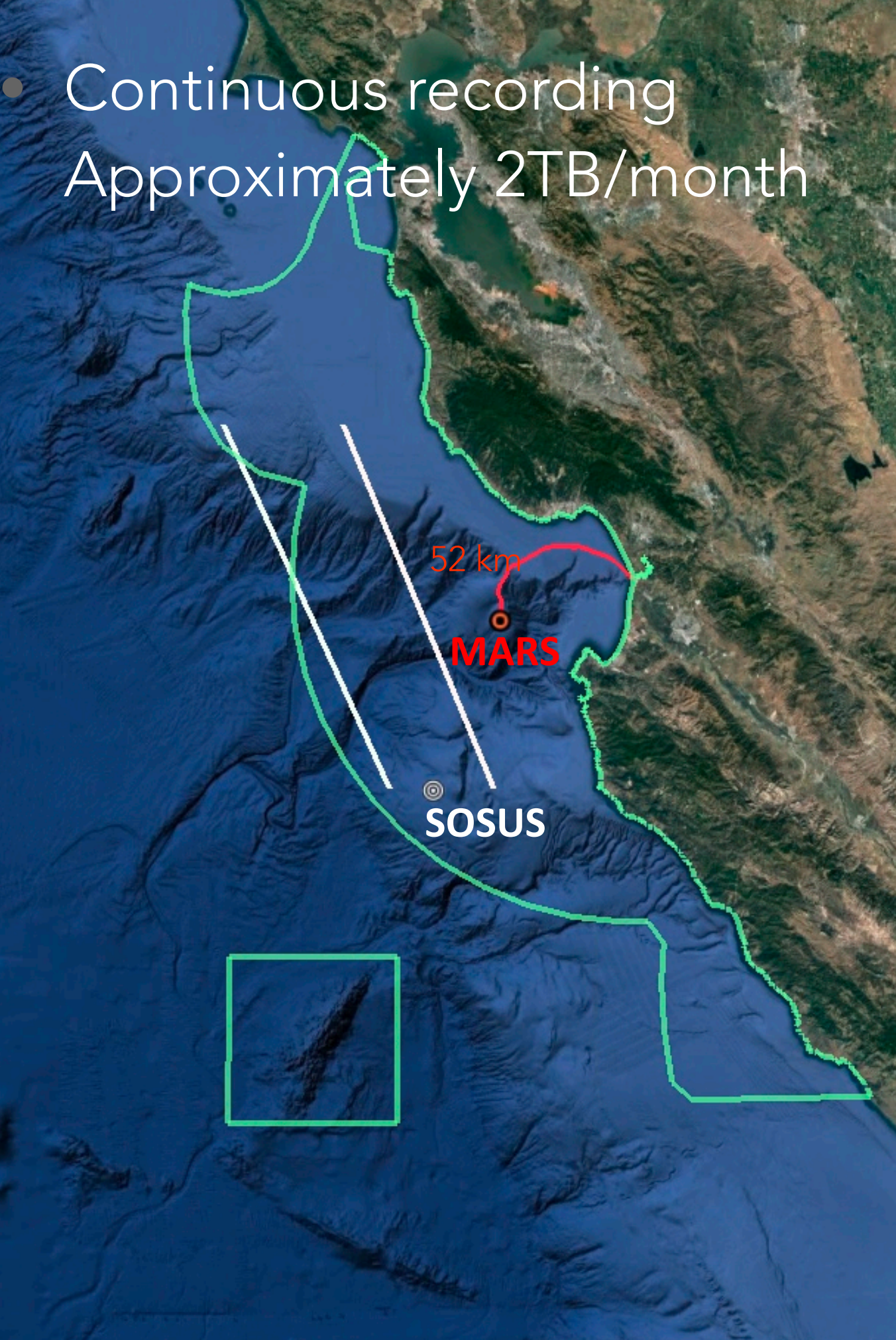
Monterey Bay Aquarium
Research Institute



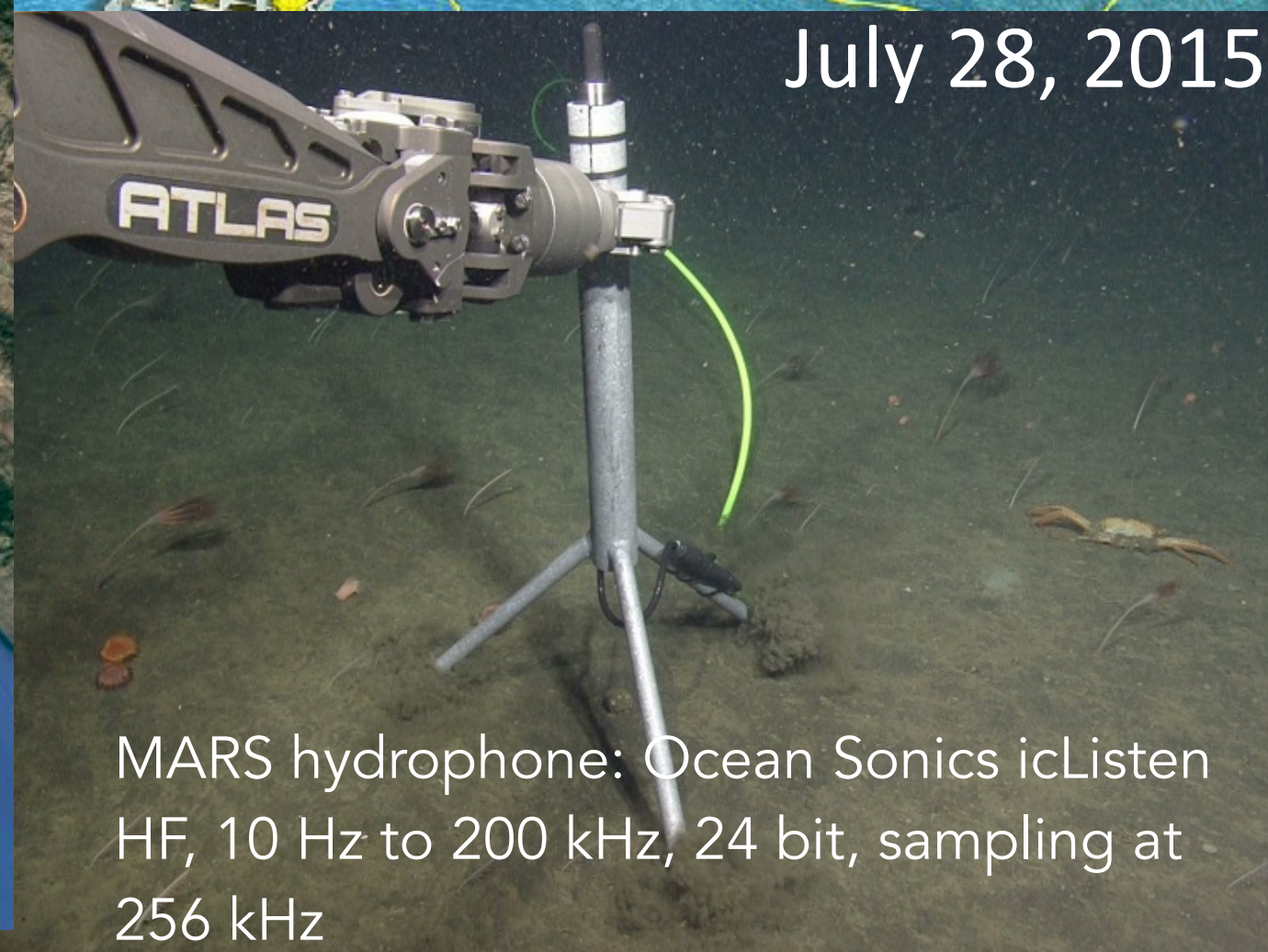
Monterey Bay Aquarium Research
Institute
7700 Sandhold Road,
Moss Landing, California



- Continuous recording
Approximately 2TB/month



Monterey Accelerated Research System (MARS)

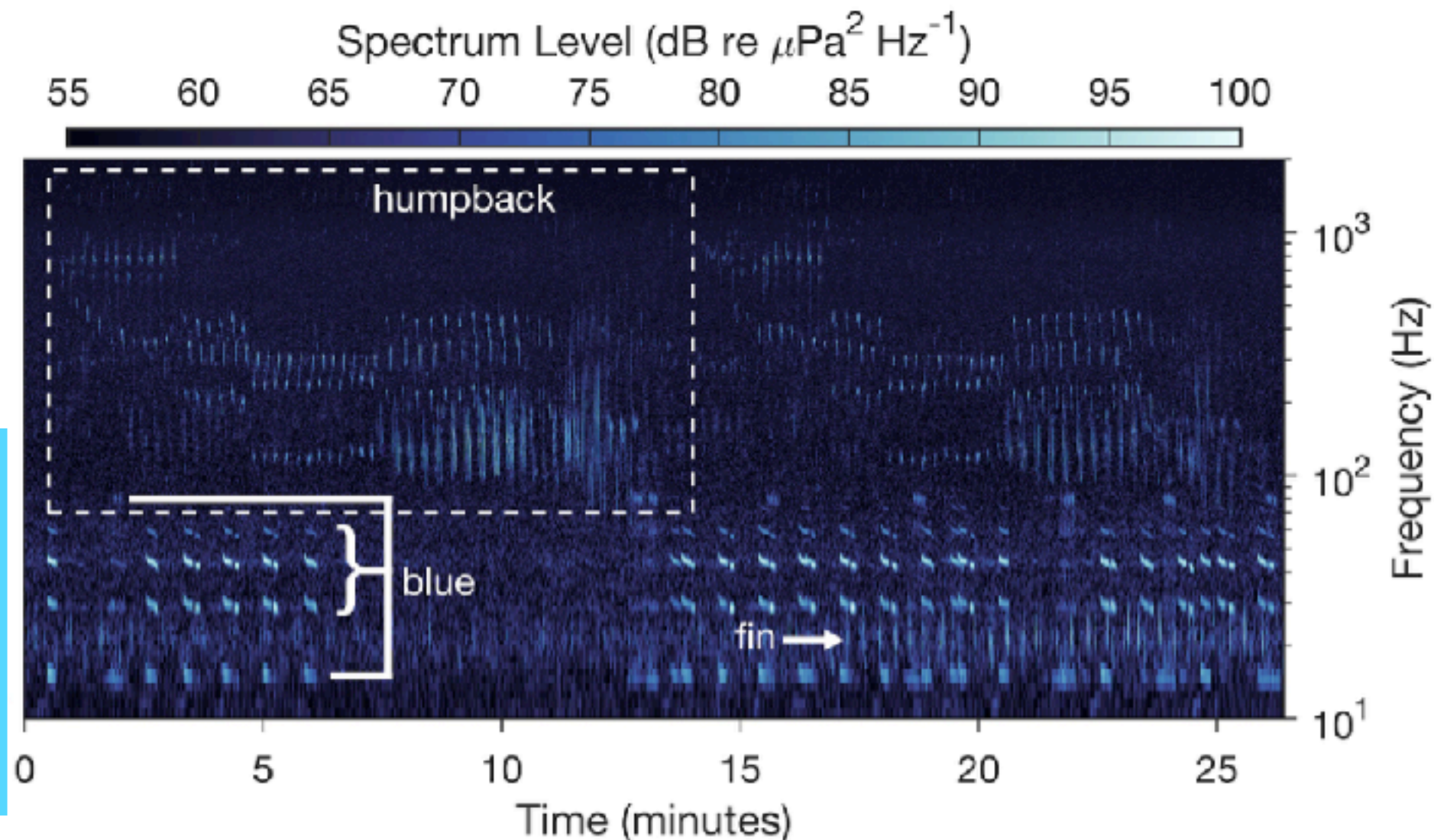
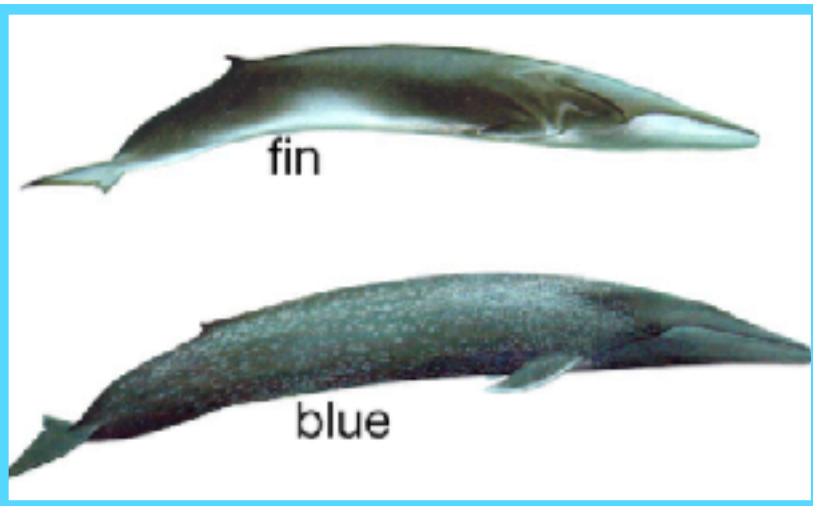


July 28, 2015

MARS hydrophone: Ocean Sonics icListen
HF, 10 Hz to 200 kHz, 24 bit, sampling at
256 kHz

GOAL

DETECTION AND CLASSIFY BLUE AND FIN WHALE CALLS

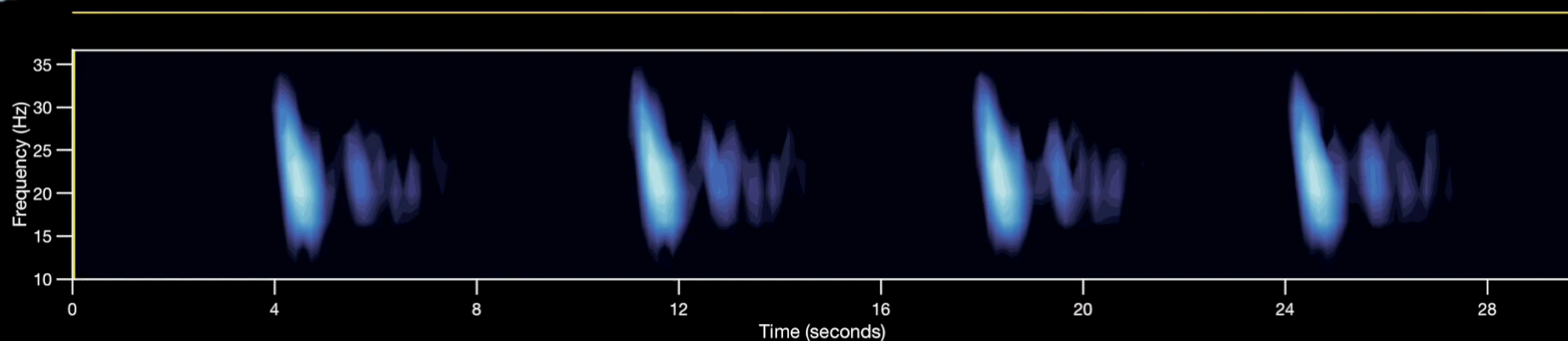


"Greyhound of the sea"

FIN WHALE

endangered

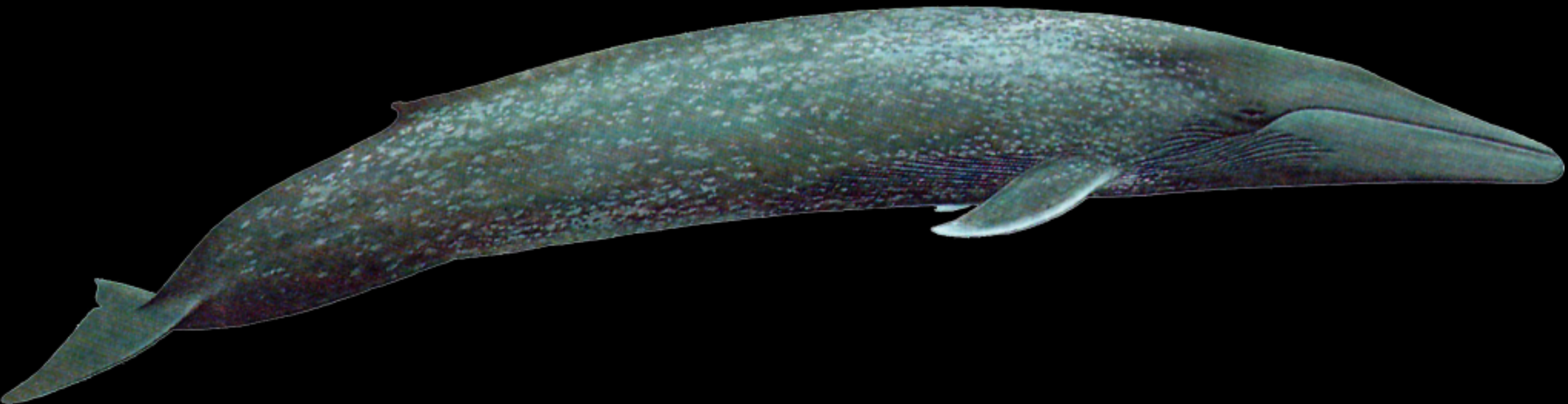
forages on schooling fish, squid, crustaceans



“Largest animal ever known to have ever existed”
- Wikipedia

BLUE WHALE

Eastern North Pacific hosts the largest population
forages on krill - up to 3,600 kg/day!



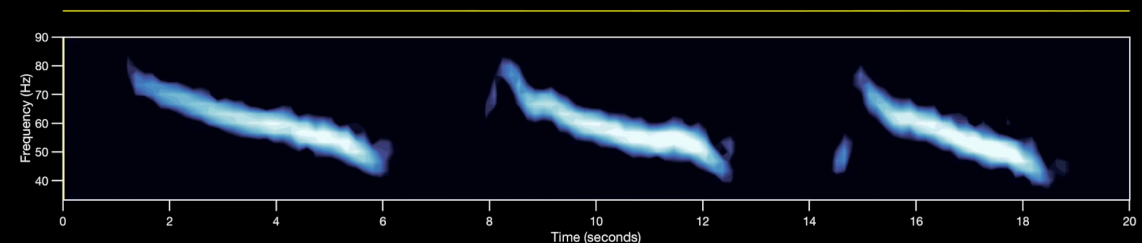
A call



B call



D call



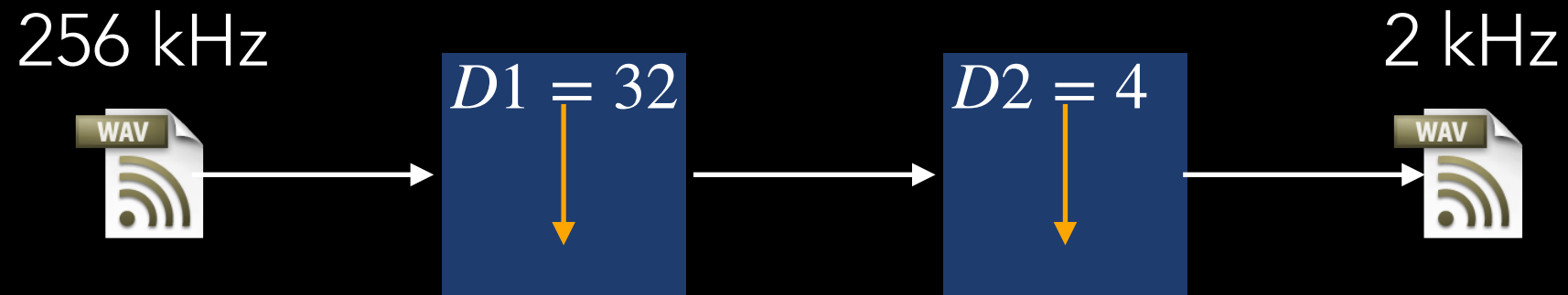
OVERVIEW

- **Data Decimation and Filtering**
- **Detection and Classification**

DECIMATION AND FILTERING

- Goal is to decimate the 256 kHz hydrophone data down to 2 kHz, a factor of 128, avoiding higher frequency aliasing
- Requires low-pass filtering the signal to limit its bandwidth to less than 1 kHz, and downsampling (i.e. throwing out 127 out of every 128 samples)
- Why not use available routines such as Matlab's decimate or Scipy's `scipy.signal.decimate`?
- We want control of the details, e.g. filter type (IIR or FIR), filter length, window type, phase linearity, etc.

DECIMATION FILTER IMPLEMENTATION DETAILS



Filtering in multiple stages is faster than a single stage

$$D1 = 2 * D * (1 - \sqrt{D * F / (2 - F)}) / (2 - F * (D + 1))$$

$$D = 128$$

$$F = f / f_{stop}$$

$$f = 100(10 \% \text{ offinalstopband})$$

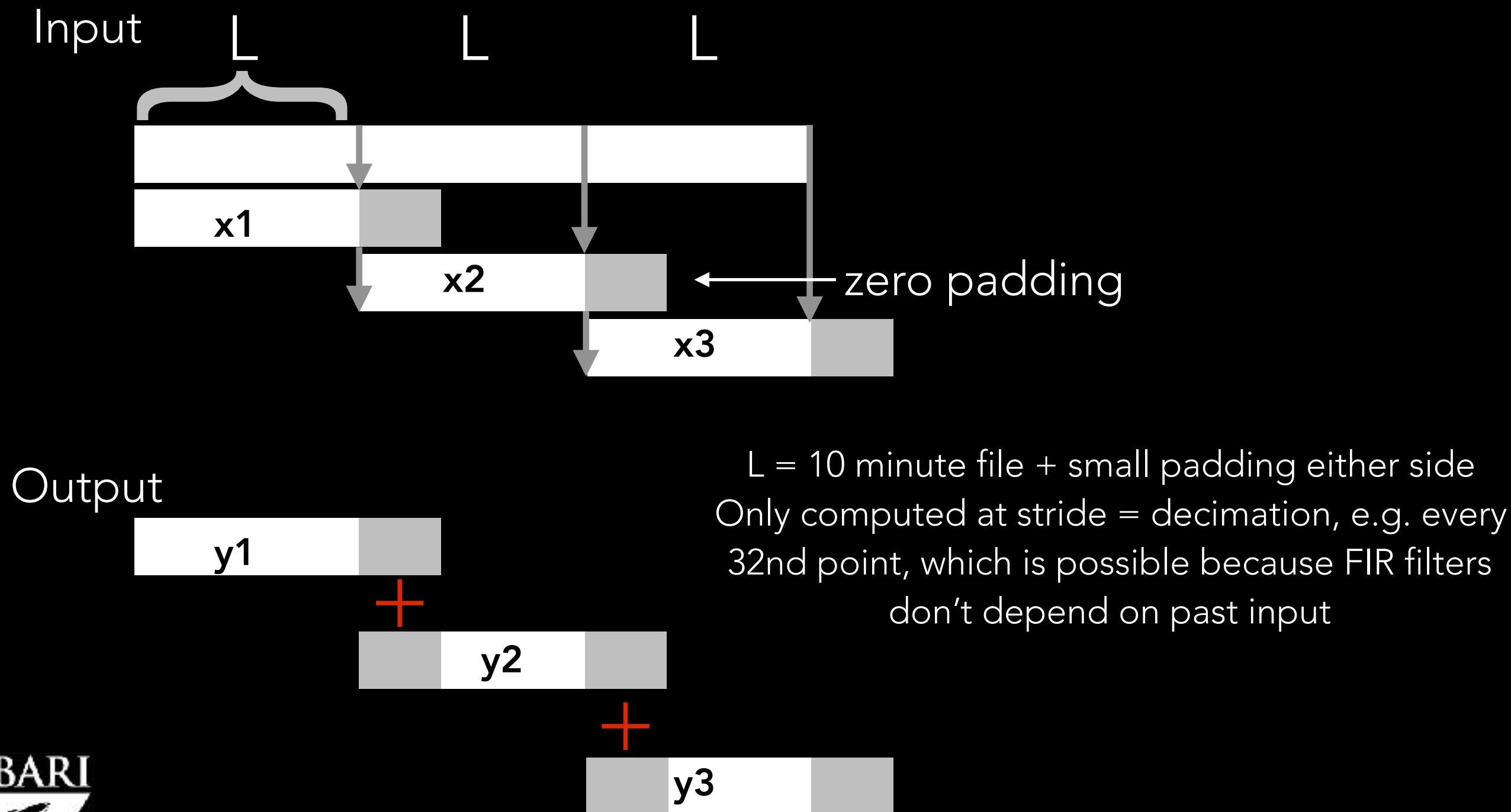
$$F = 100 / 1000$$



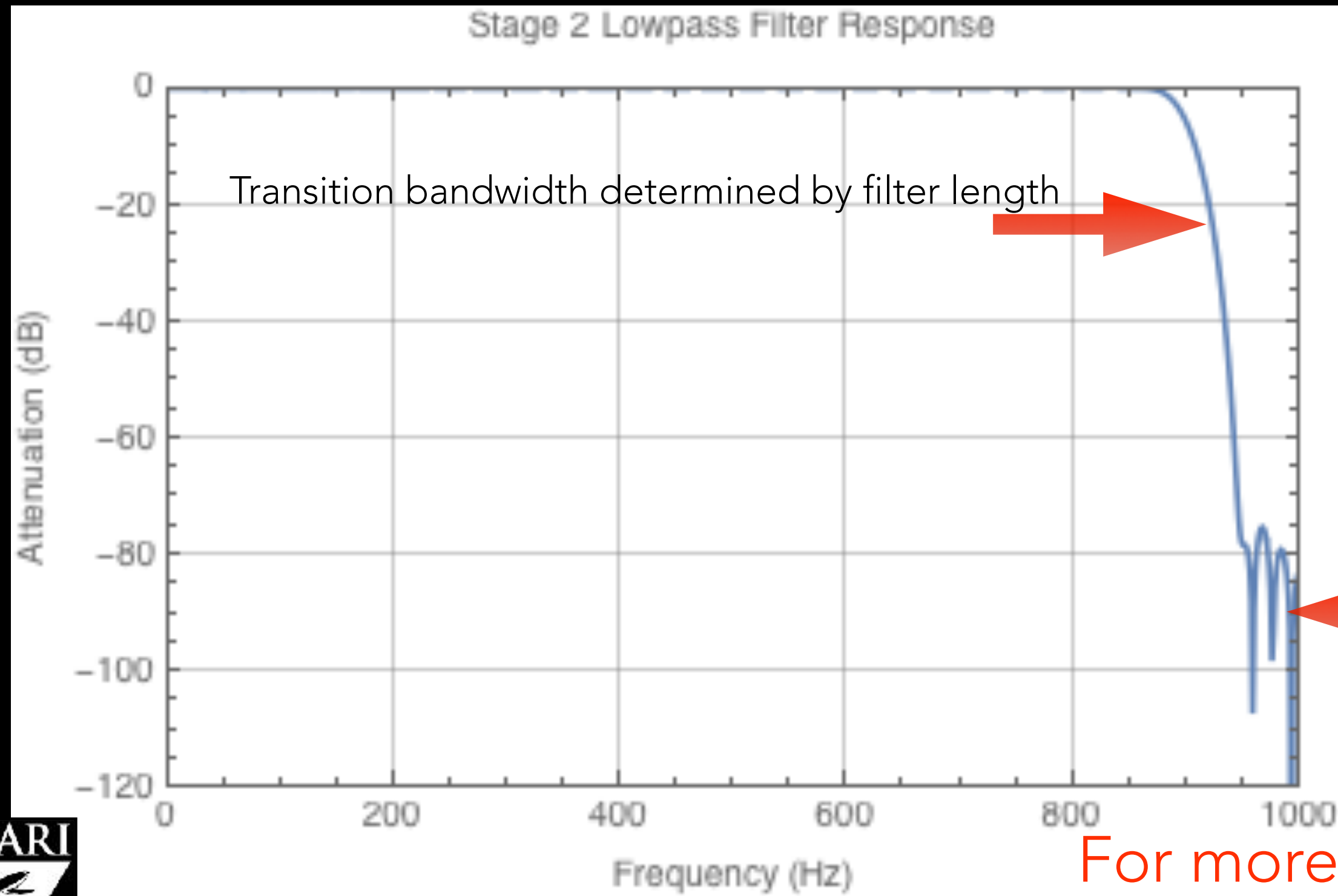
*Lyons, R. G. (2004). *Understanding digital signal processing* (2nd ed.). Upper Saddle River, NJ: Prentice Hall

<https://bitbucket.org/mbari/pam-decimate-notebook>

DECIMATION FILTER IMPLEMENTATION DETAILS



DECIMATION FILTER



<https://bitbucket.org/mbari/pam-decimate-notebook>

DETECTION AND CLASSIFICATION

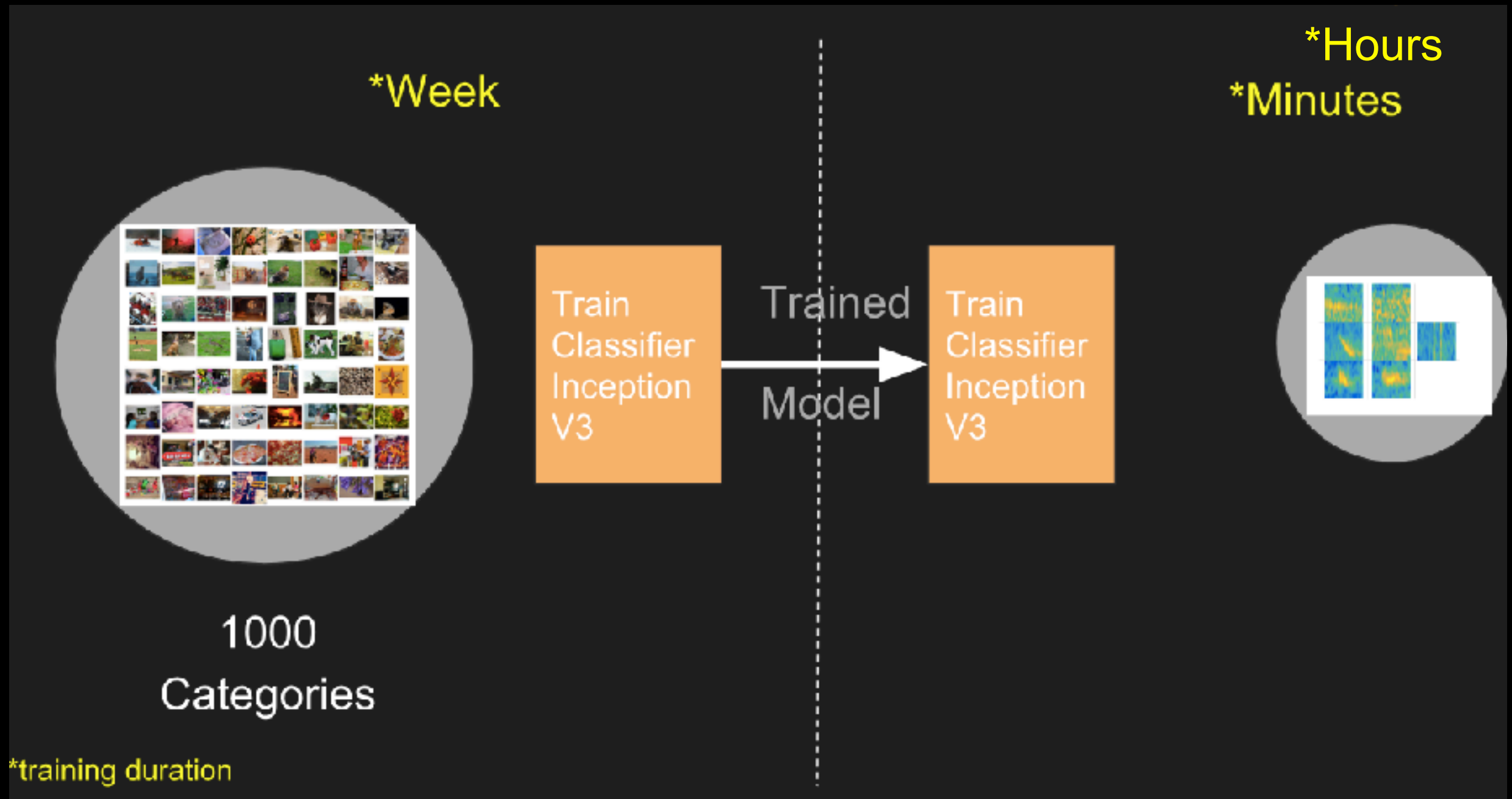
- **Detect** candidate calls using Band-Limited-Energy-Detectors *(simple, fast to compute, not very intelligent)*
- **Classify** candidate calls using transfer learning
(more intelligent)

BAND-LIMITED ENERGY DETECTOR - TWO-STAGE APPROACH

- Stage 1: find every sequence of consecutive spectral slices where the in-band power exceeds a specified threshold
- Stage 2: candidates that are too short, too long, or too sparse (occupancy is below the specified threshold) are discarded
- Don't expect perfection with this method. This requires iteration. Raven simplifies this process with an interactive tool.



DETECTION AND CLASSIFICATION

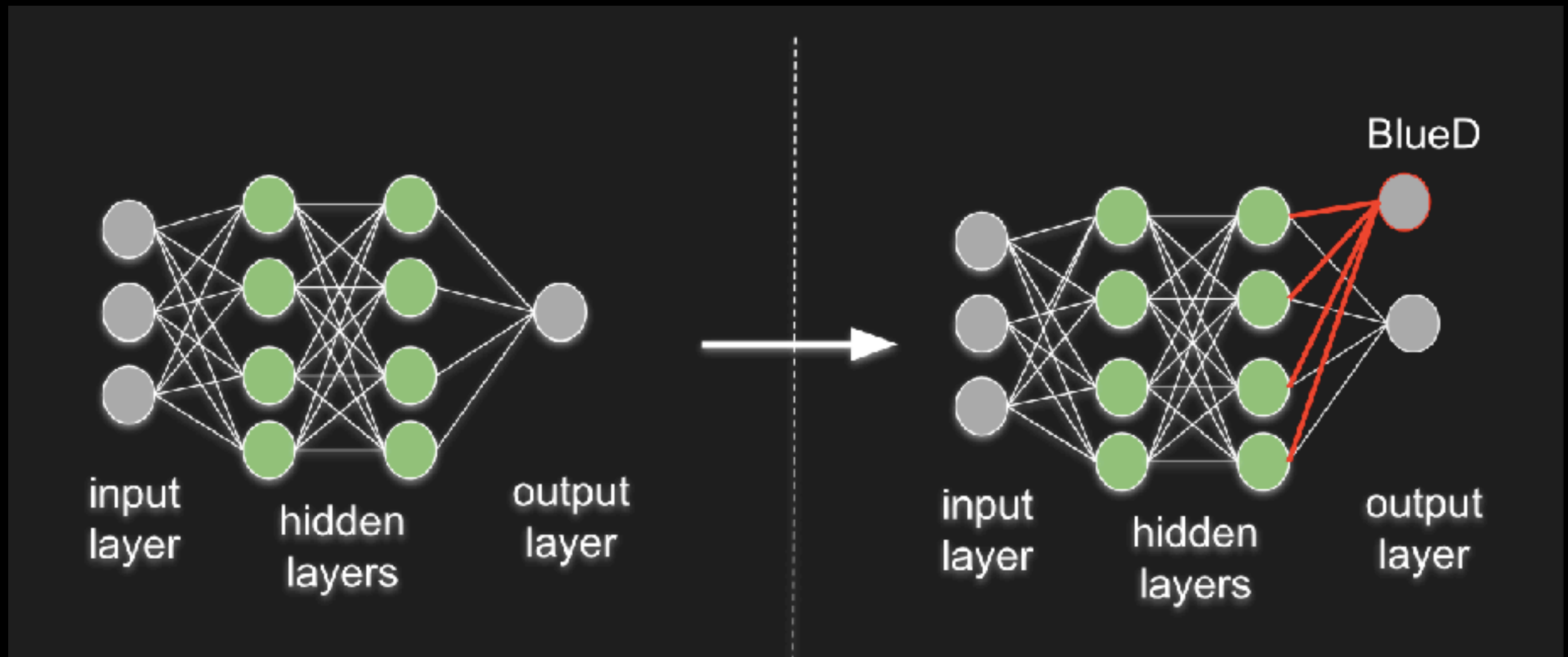


Transfer Learning Concept

Start with pre-trained model (this may have taken a week to train, but you don't need to worry about that)

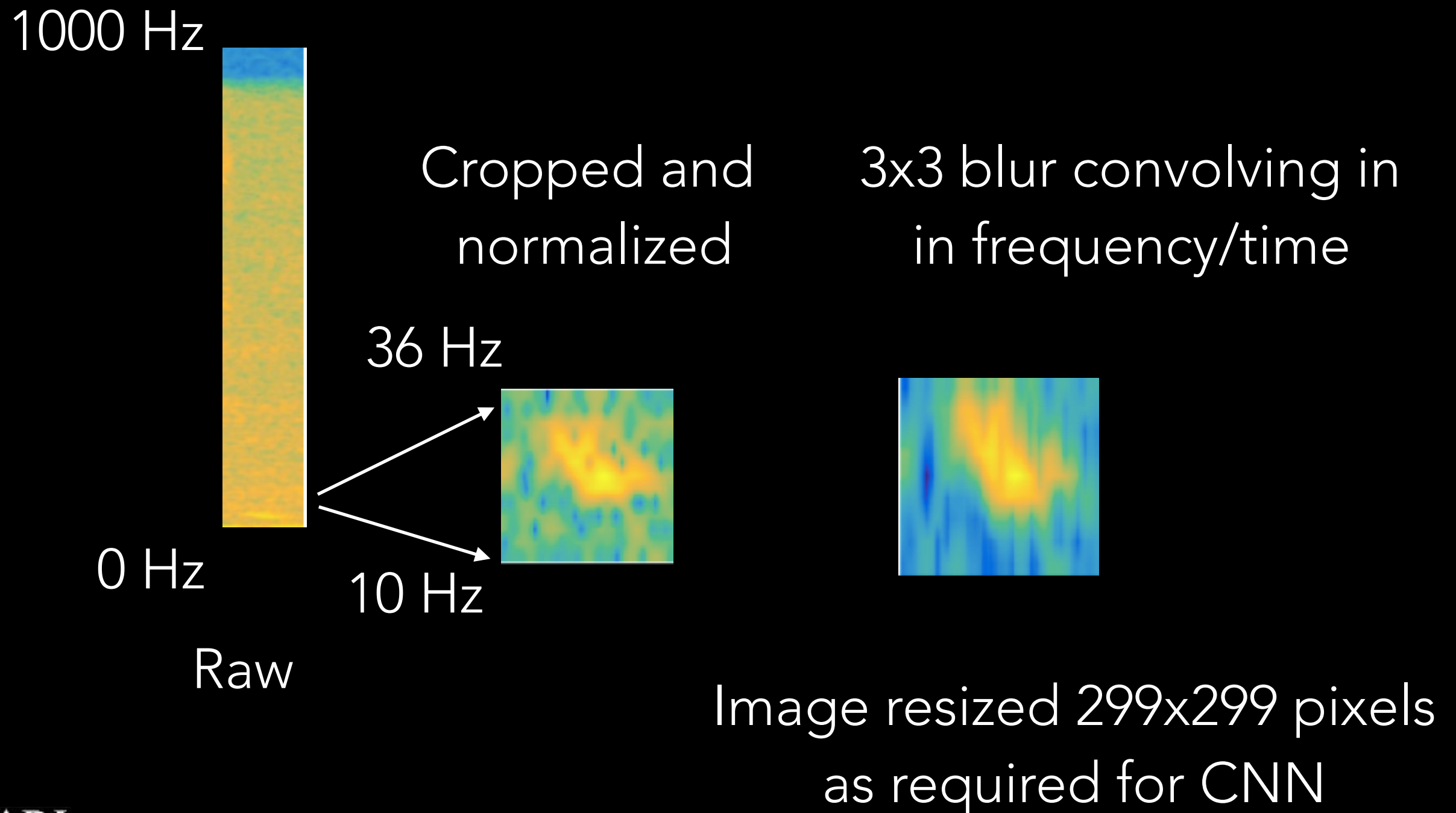
train, or "fine-tune" for the problem of whale classification

DETECTION AND CLASSIFICATION



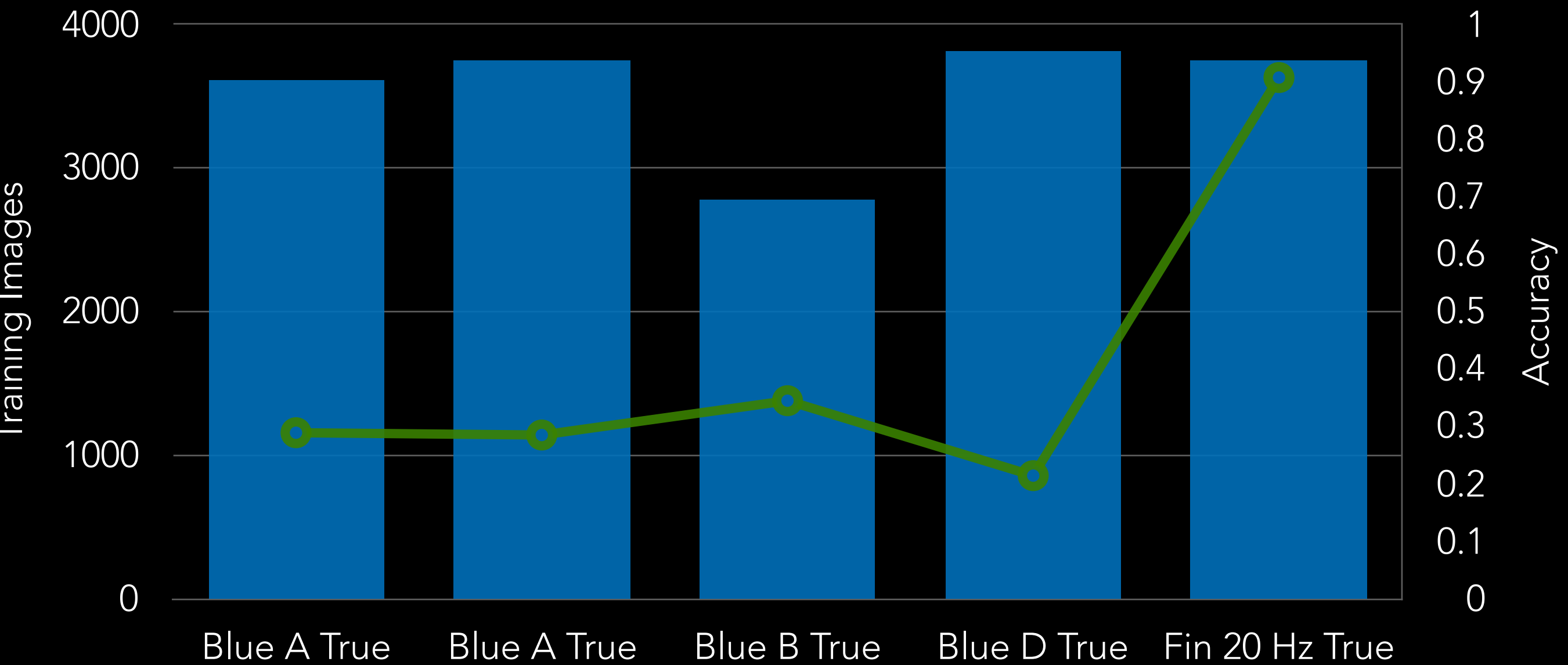
Retrain the output dense layers only

SPECTROGRAM ENHANCEMENT



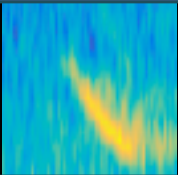
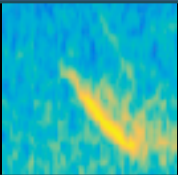
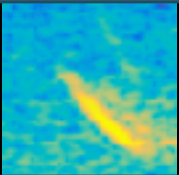
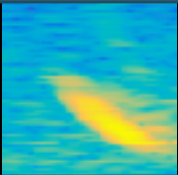
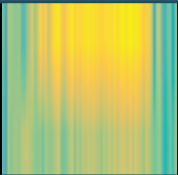
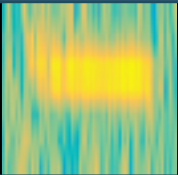
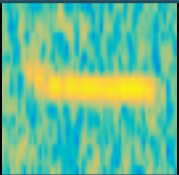
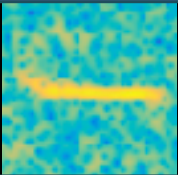
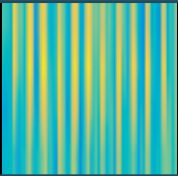
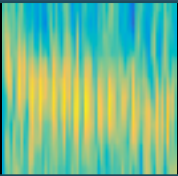
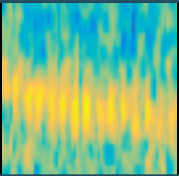
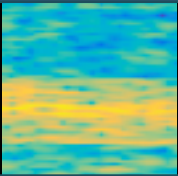
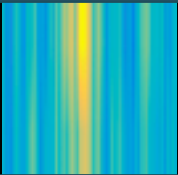
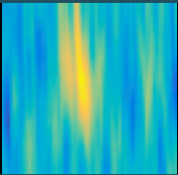
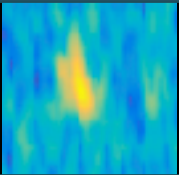
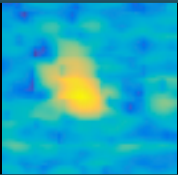
CLASSIFICATION ACCURACY

ACCURACY 80/20 TRAIN/TEST SPLIT, 30K STEPS, RANDOM CROP



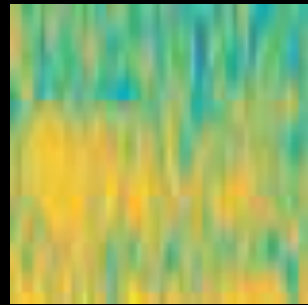
CLASSIFICATION VARYING FFT LENGTHS

AVERAGE ACCURACY 80/20 TRAIN/TEST SPLIT, 30K STEPS, RANDOM CROP

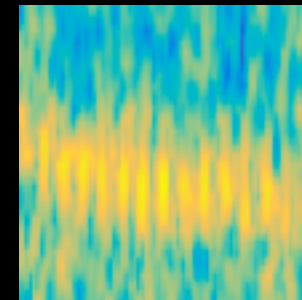
	FFT LENGTH, 0.95% OVERLAP, HANNING			
	512	1024	2048	4096
BLUE D	0.967	0.952	0.953	0.919
				
BLUE B	0.637	0.643	0.631	0.669
				
BLUE A	0.953	0.938	0.95	0.96
				
FIN 20 H7	0.893	0.907	0.895	0.909
				



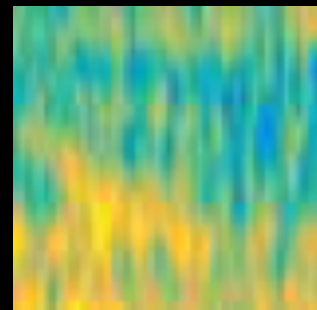
MISCLASSIFICATIONS



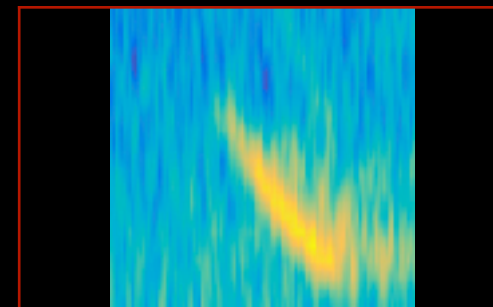
Blue A True
(predicted as false)



Example

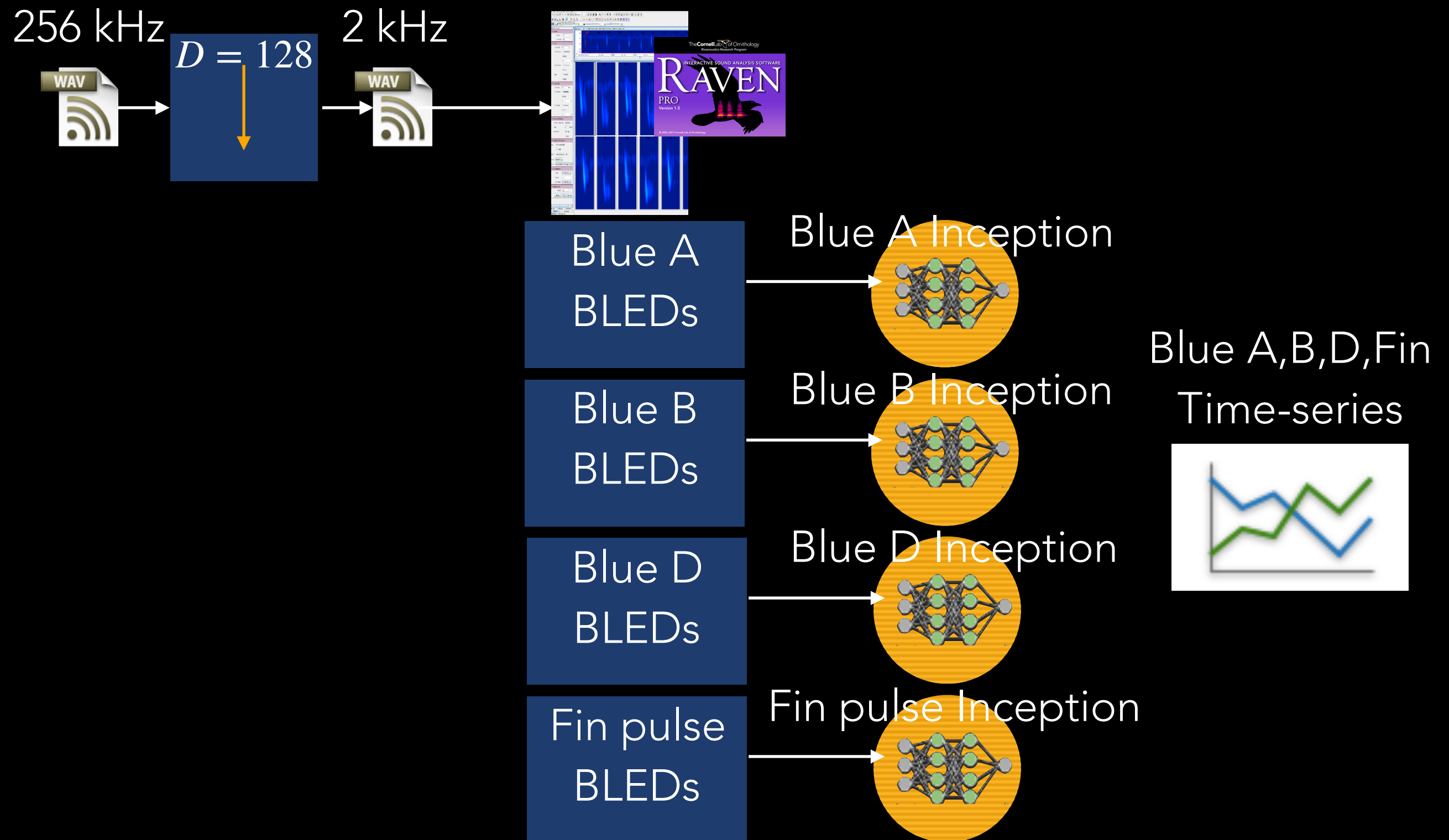


Blue D True
(predicted as False)



Example

DECIMATION, DETECTION AND CLASSIFICATION WORKFLOW



CONCLUSIONS

- BLED can difficult to fine-tune. Verbose detections required for accurate classification. Sensitive to noise.
- High classification accuracy for most classes. More training data and curation should improve accuracy.

FUTURE WORK

- Refine and augment training libraries (using existing models)
- Run entire 3 year time-series
- Explore replacing BLEED with ResNet-50
- Evaluate per-channel energy normalization (PCEN) as method to suppress noise



THANK YOU

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PhD Student
Stanford University
Hopkins Marine Station

