Methods to Overcome Data Scarcity

Bruno Padovese

Problem Statement

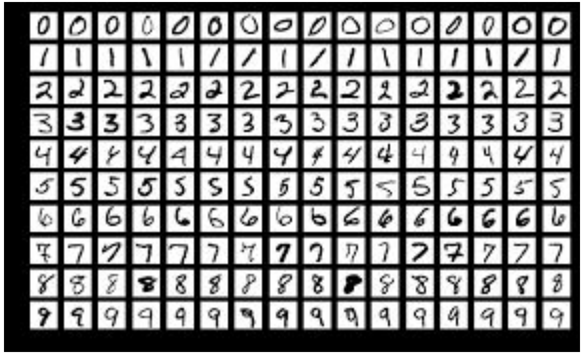
- Deep Learning has been shown to provide excellent results
  - Text (translation, negotiations...)
  - Voice identification and Recognition
  - Video (object identification, lip reading...)
  - Image classification and generation

- However, a major bottleneck exists
  - Deep Learning requires large amounts of data!

Source: feedthedatamonster.com

Datasets in Modern Deep Learning

CIFAR 10



IMAGENET

- Very high quality benchmarks datasets

Problem Statement

- Data quality is also critical in Machine Learning applications
    - In reality, most datasets will be very far away from ideal

- Collecting data is a hard and time-consuming task. High quality data, doubly so

- In the realm of bioacoustic it gets even harder
    - Remote, inhospitable locations
    - Manpower heavy, even with the help of Passive acoustic monitoring
    - Costly

Problem Statement

- Bioacoustics also presents an additional bottleneck: annotating large amounts of raw data
    - Multiple sensors from PAM systems can produce an insurmountable amount of data to manually label
    - Only a fraction of the data is actually useful
    - Many Datasets could only been 1% annotated

- How can we mitigate this problem? Collect more data? Annotate more data?

- Recently, several approaches have been proposed to diversify our datasets

Data Augmentation

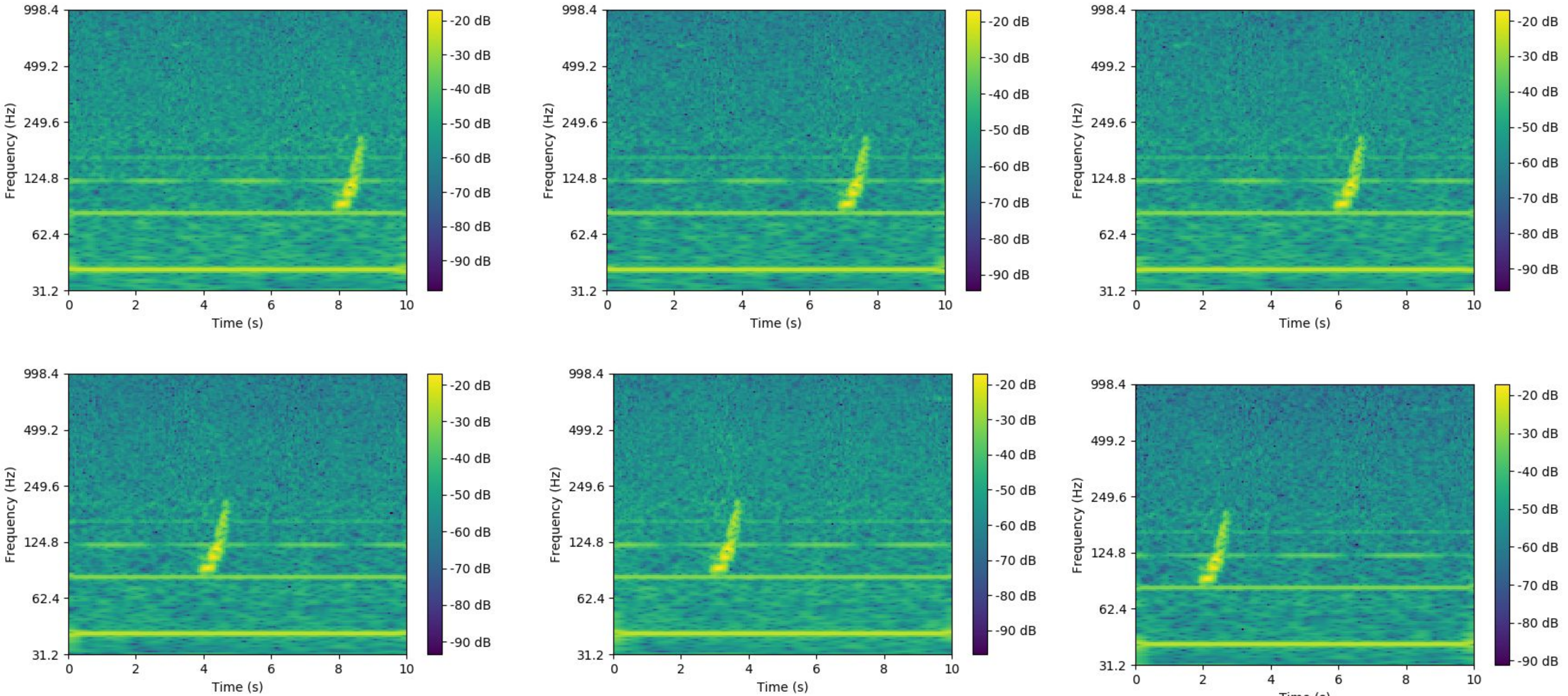
Data Augmentation

- Data Augmentation are techniques that can be employed to increase the size and diversity of our datasets
    - Ways to artificially generate data while still being realistic

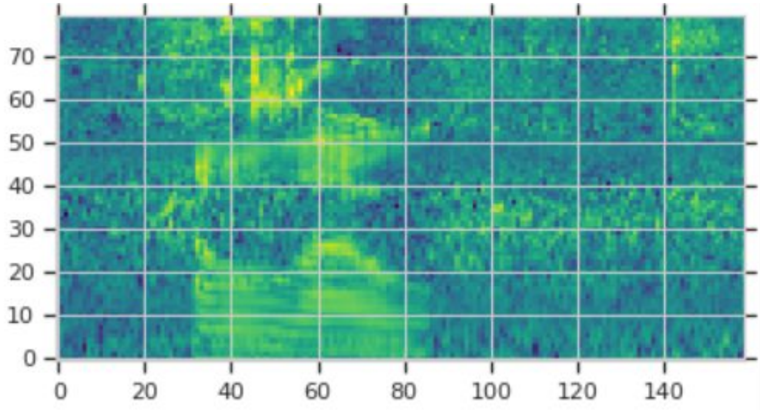
- Can be used to increase performance of models to generalize
    - Introduces new data to the training set

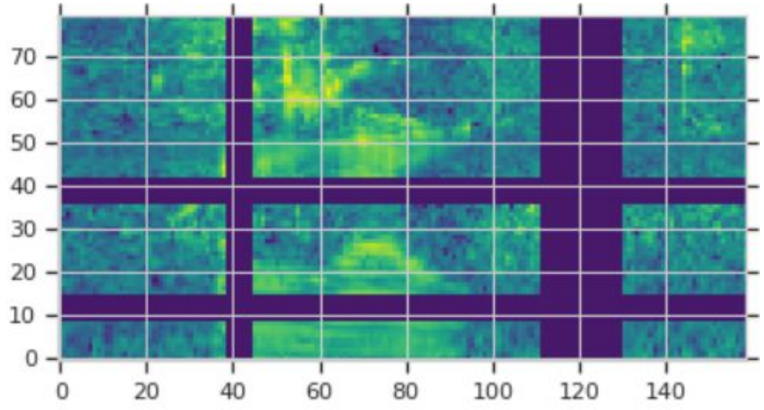
- Methods range from trivial to complex, both presenting good results

Data Augmentation - Shifting time domain



Data Augmentation - Spec Augment





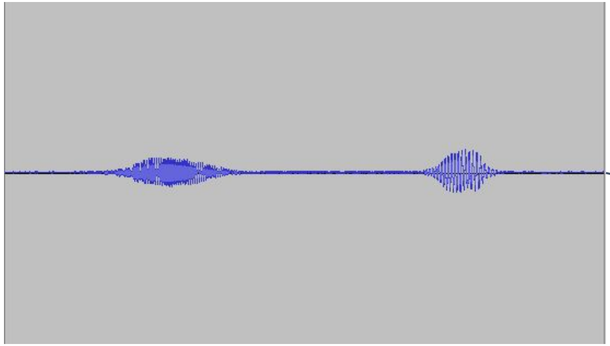
Data Augmentation

- When dealing with Audio, augmentation techniques can be applied in the spectrogram domain or directly to the waveform or both
    - Shifting and SpecAugment are examples of spectrograms augmentation

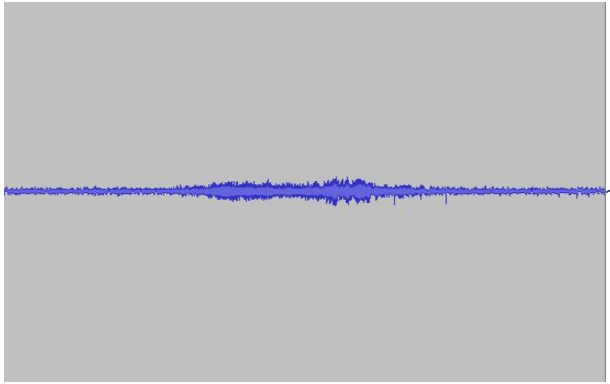
- Techniques applied to the waveform are also widely used

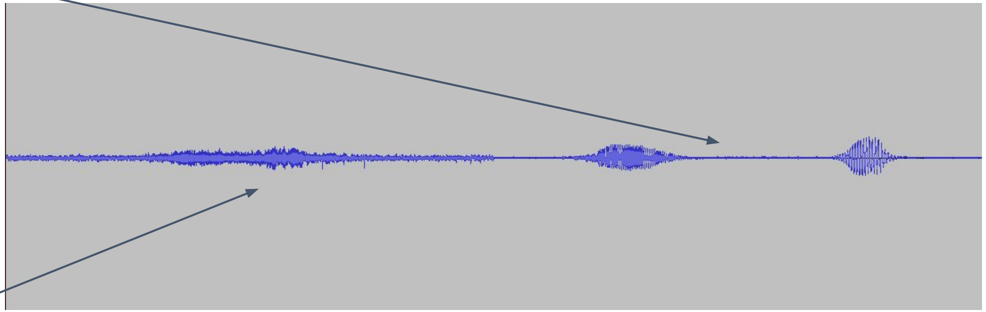
Data Augmentation - Mixup

Humpback Whale

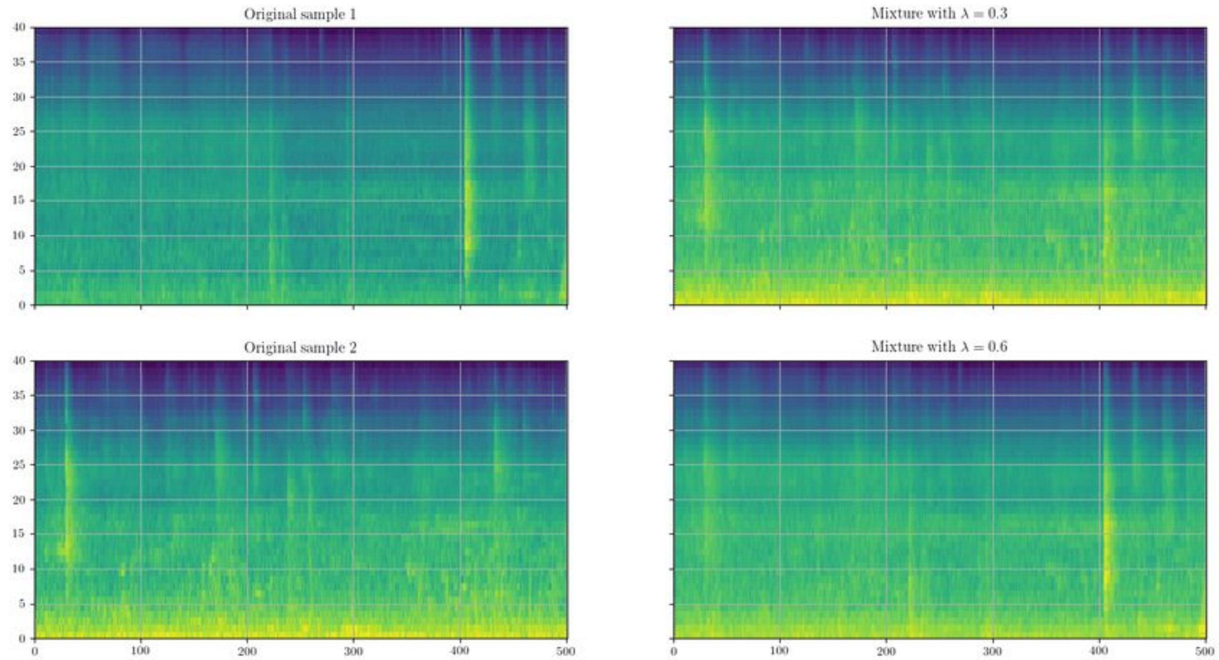


Northern Right Whale





Data Augmentation - Mixup



Data Augmentation

- Changing the spectrogram generation parameters can also yield different representations of the same signal
  - Different spectral resolutions to be able to distinguish different spectral features

- Augmentation has become a default pre-processing step in many fields
  - DCASE - Detection and Classification of Acoustic Scenes and Events
  - SpecAugment and Mixup being used in most works

Data Augmentation

- Simple methods that significantly increases performance of deep learning models

- Data Augmentation should not and will not replace real data!
    - Efforts towards collecting and labelling more data should continue
    - Data Augmentation tries to fill gaps present in current datasets
    - Augmented data is used alongside real data in training procedures
    - Methods are only as good as the data they try to match

Few-shot Learning

Few-shot learning

Meta-learning

Learn a learning strategy to adjust well to a new few-shot learning task

Metric learning

Learn a semantic embedding space using a distance loss function

Data augmentation

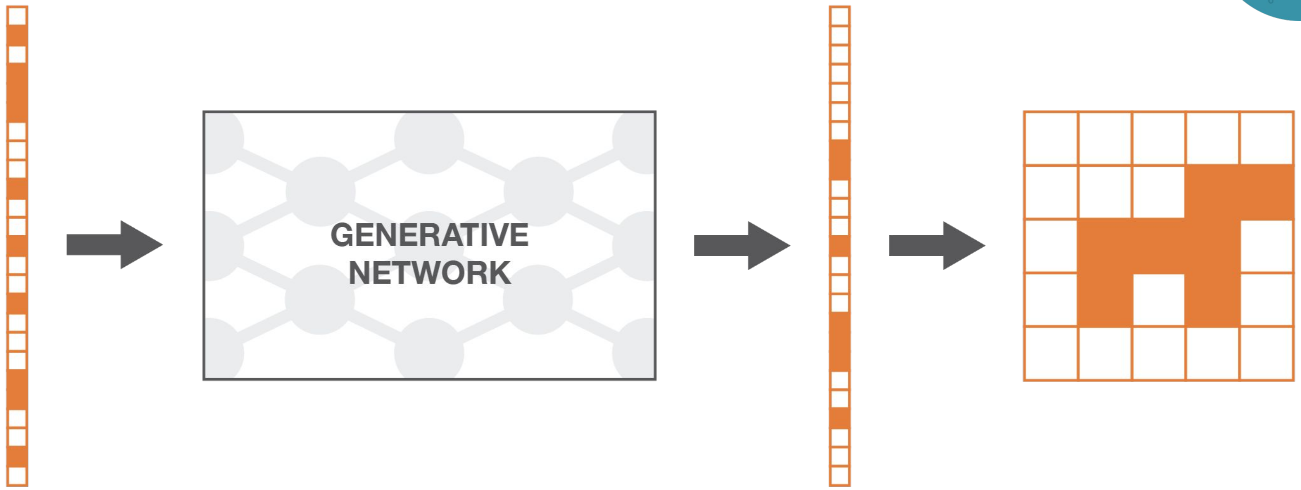
Synthesize more data

GANs (Generative Adversarial Networks) and WaveNet

Generative Models

Generative Models

Generative Models



Input random variable (drawn from a simple distribution, for example uniform).

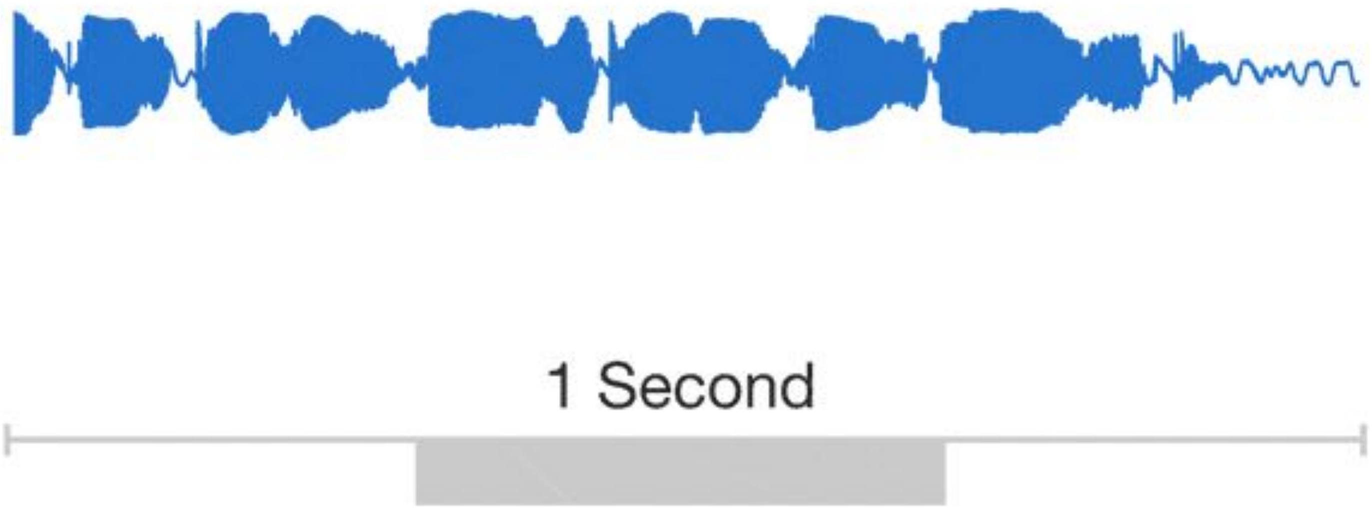
The generative network transforms the simple random variable into a more complex one.

Output random variable (should follow the targeted distribution, after training the generative network).

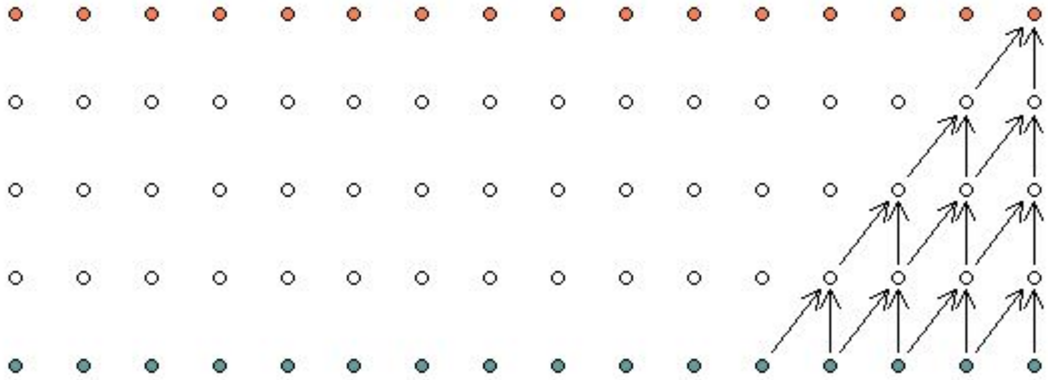
The output of the generative network once reshaped.

Source: https://towardsdatascience.com/understanding-generative-adversarial-networks-gans-cd6e4651a29

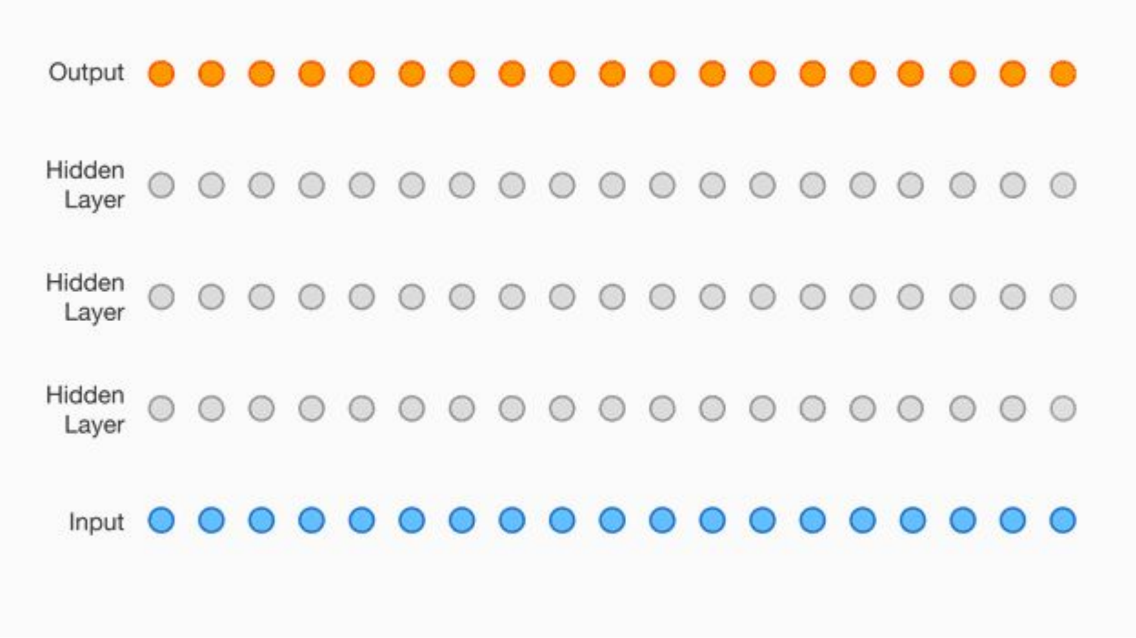
Generative Models - WaveNets



Non dilated Causal Convolutions



Generative Models - WaveNets

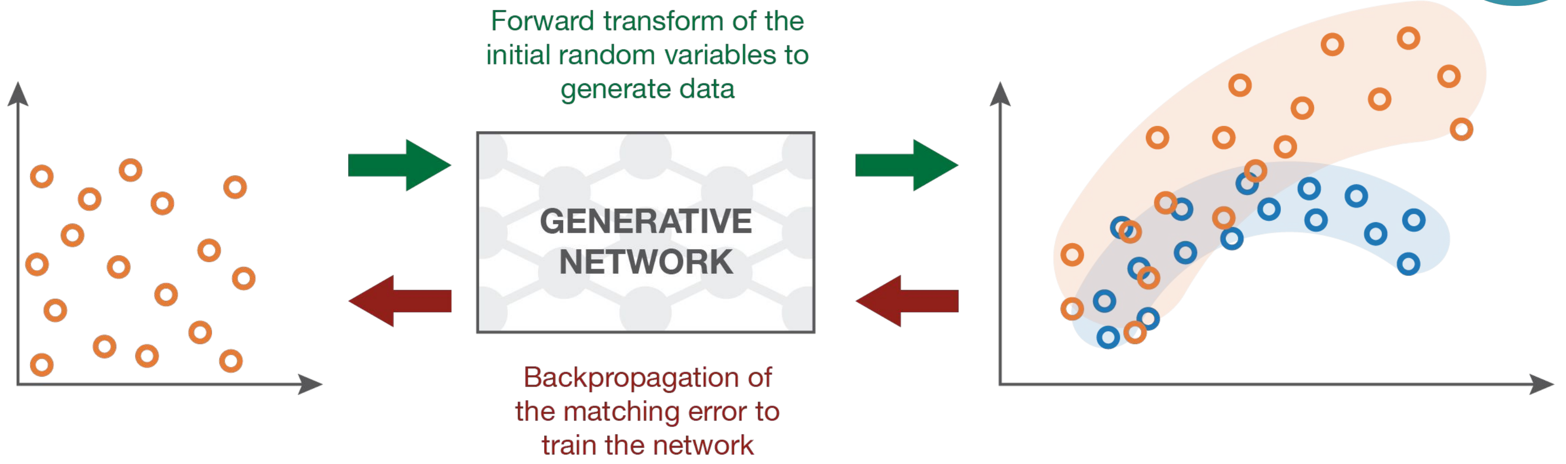


Generative Models - WaveNets

Will these types of method work well in bioacoustics with little modification?

- Can it be used to generate a whale upcall for example?

GANs



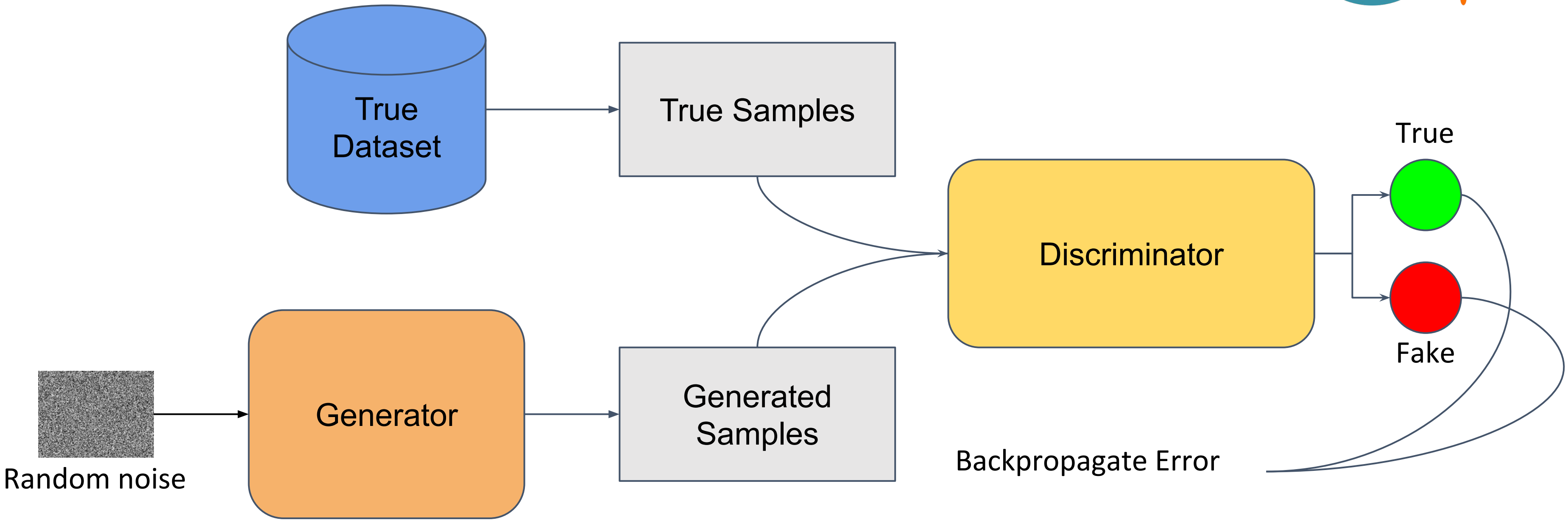
Input random variables (drawn from a uniform).

Generative network to be trained.

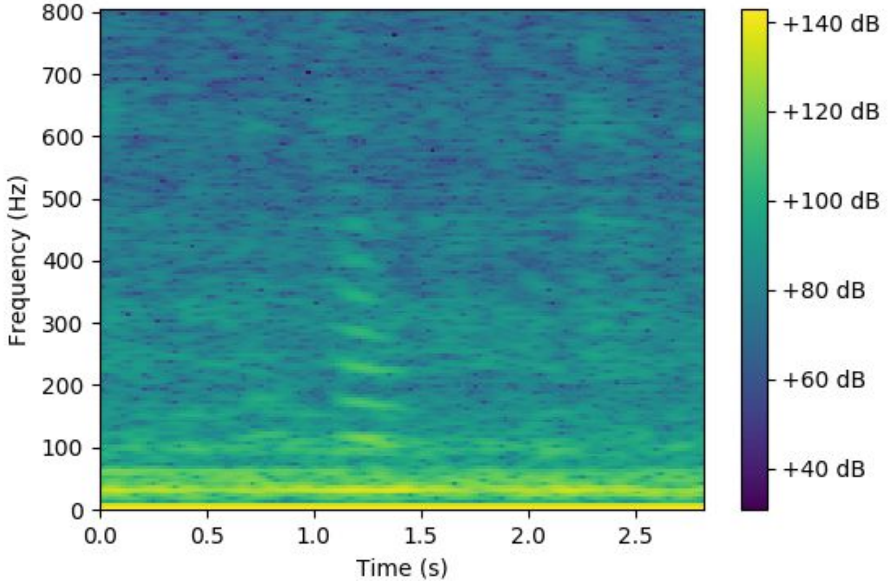
The generated distribution is compared to the true distribution and the "matching error" is backpropagated to train the network.

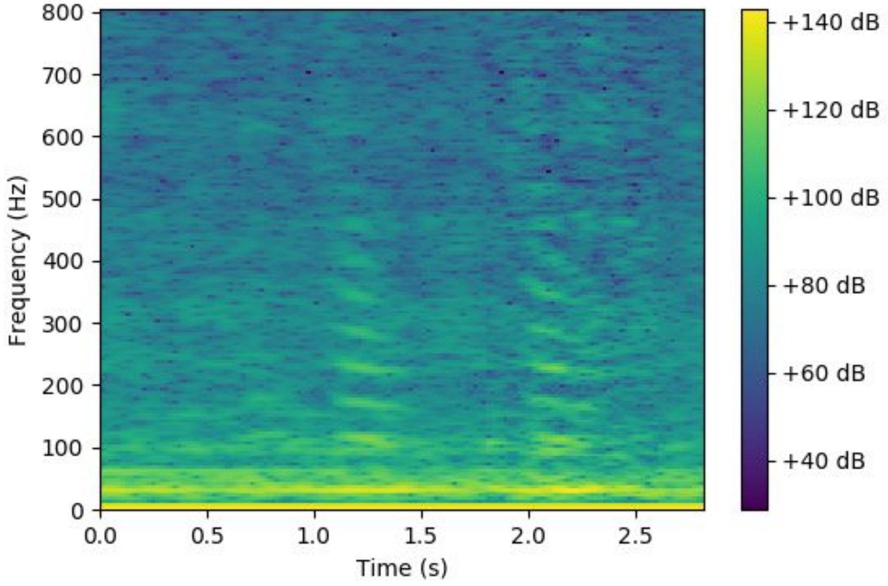
Source: https://towardsdatascience.com/understanding-generative-adversarial-networks-gans-cd6e4651a29

GANs


True
Dataset
True Samples
Discriminator
True
Fake
Random noise
Generator
Generated
Samples
Backpropagate Error

Data Augmentation





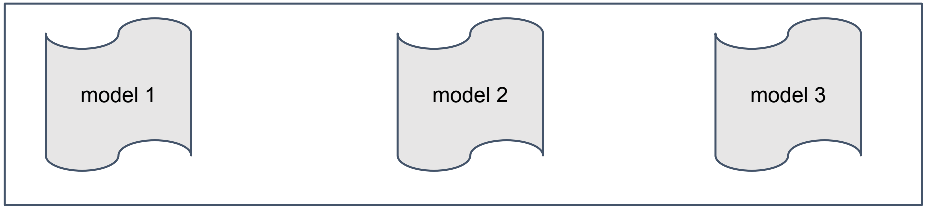
Questions

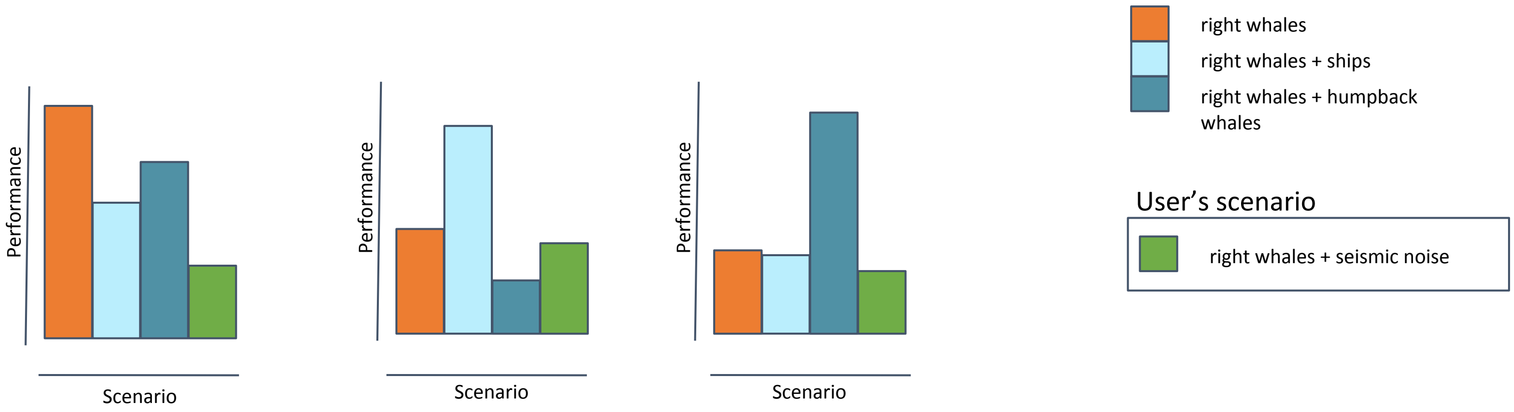
- How good do these generators need to be?
- How much data do you need to achieve good generations?
- How much augmentation do you need? What type?

How does it relate to Meridian?

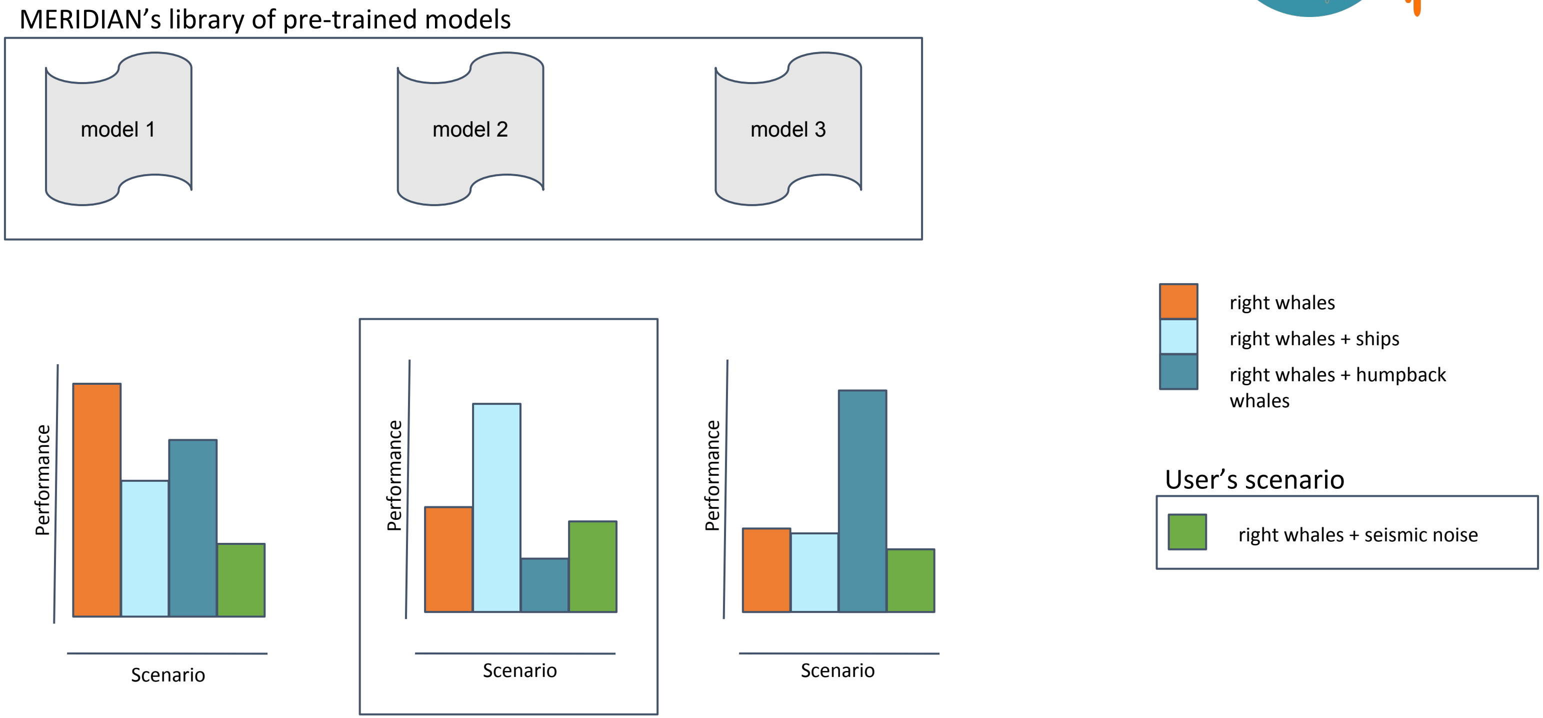
Workflow visions

MERIDIAN’s library of pre-trained models



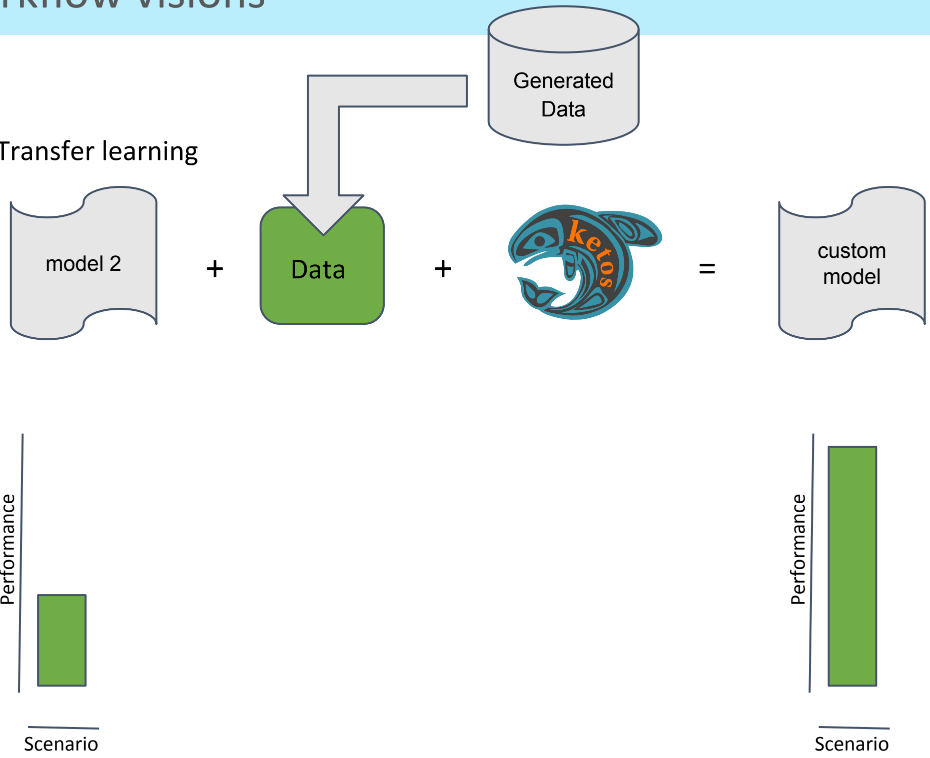


Workflow visions

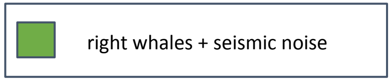


Workflow visions

Transfer learning



User's scenario



Thank you