Deep Learning Approach to Bottom Correction from Sonar Data

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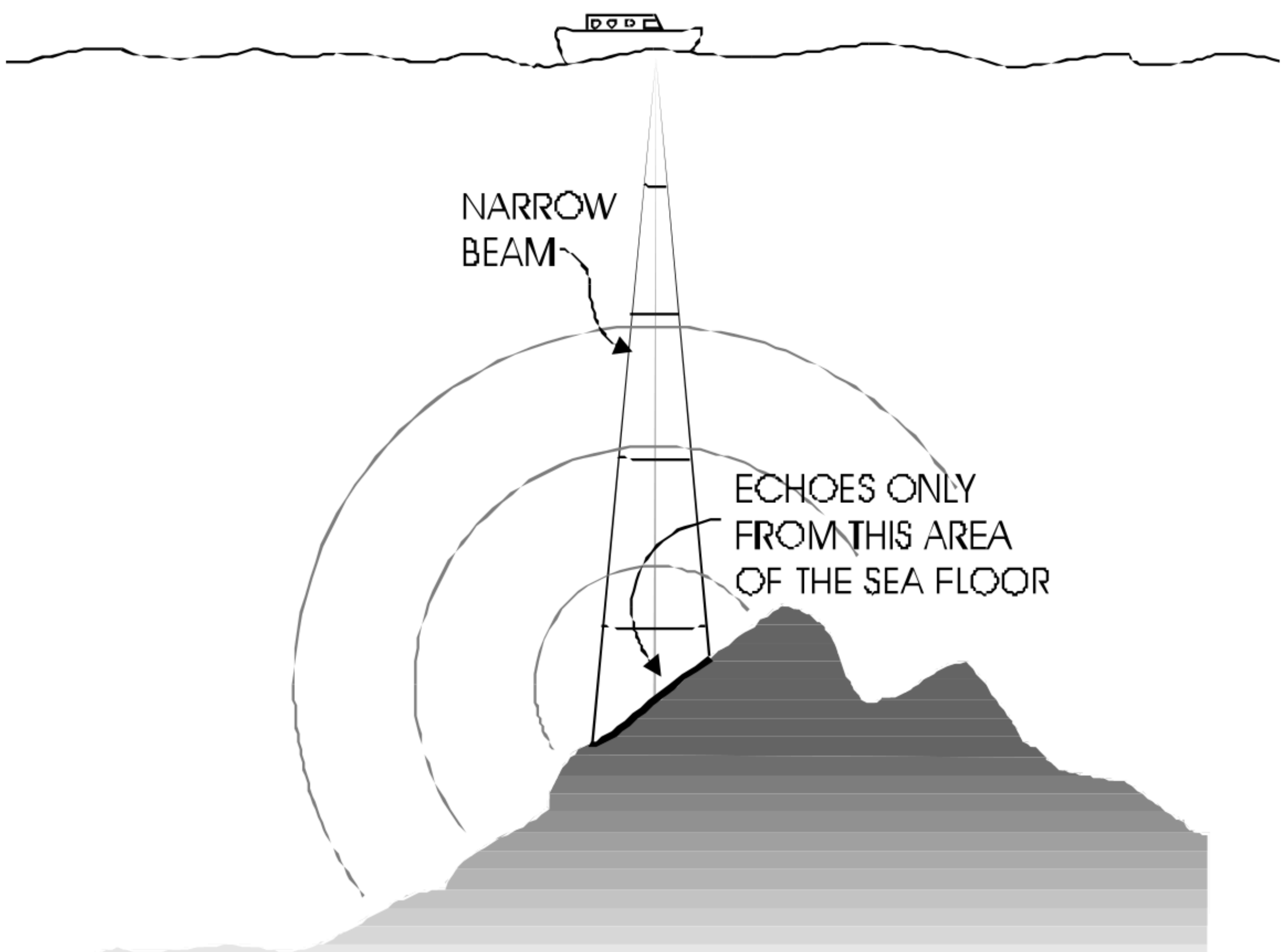
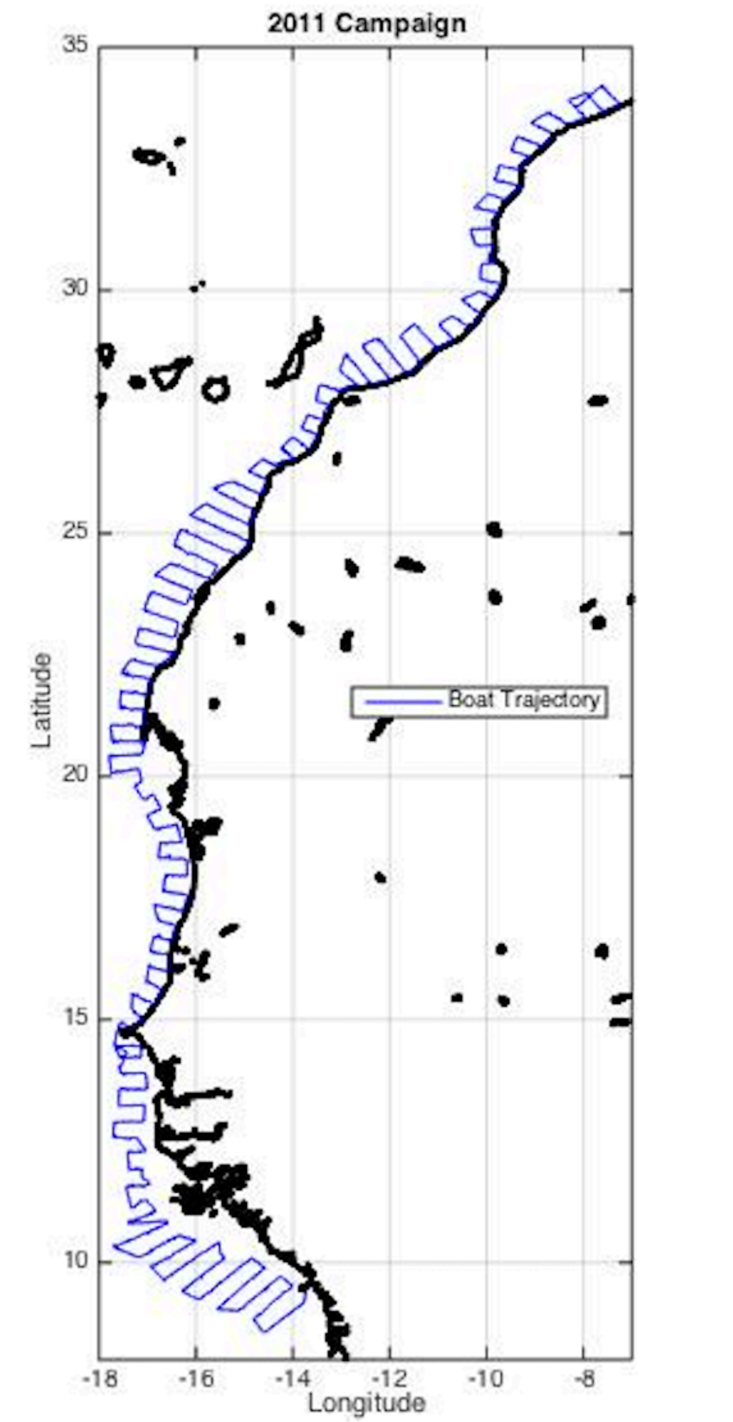
Background and Motivation

Data acquisition

Data are acquired with an echo sounder. The vessel sends out pulses of various frequency's **acoustic waves in the water**, those waves are **reflected back** to the source **when they meet** diverse organisms (fish, plankton, etc) or more generally **solid objects**. We call **a ping (or echo) the corresponding signal, and echogram** the whole dataset generated by this procedure on a campaign.

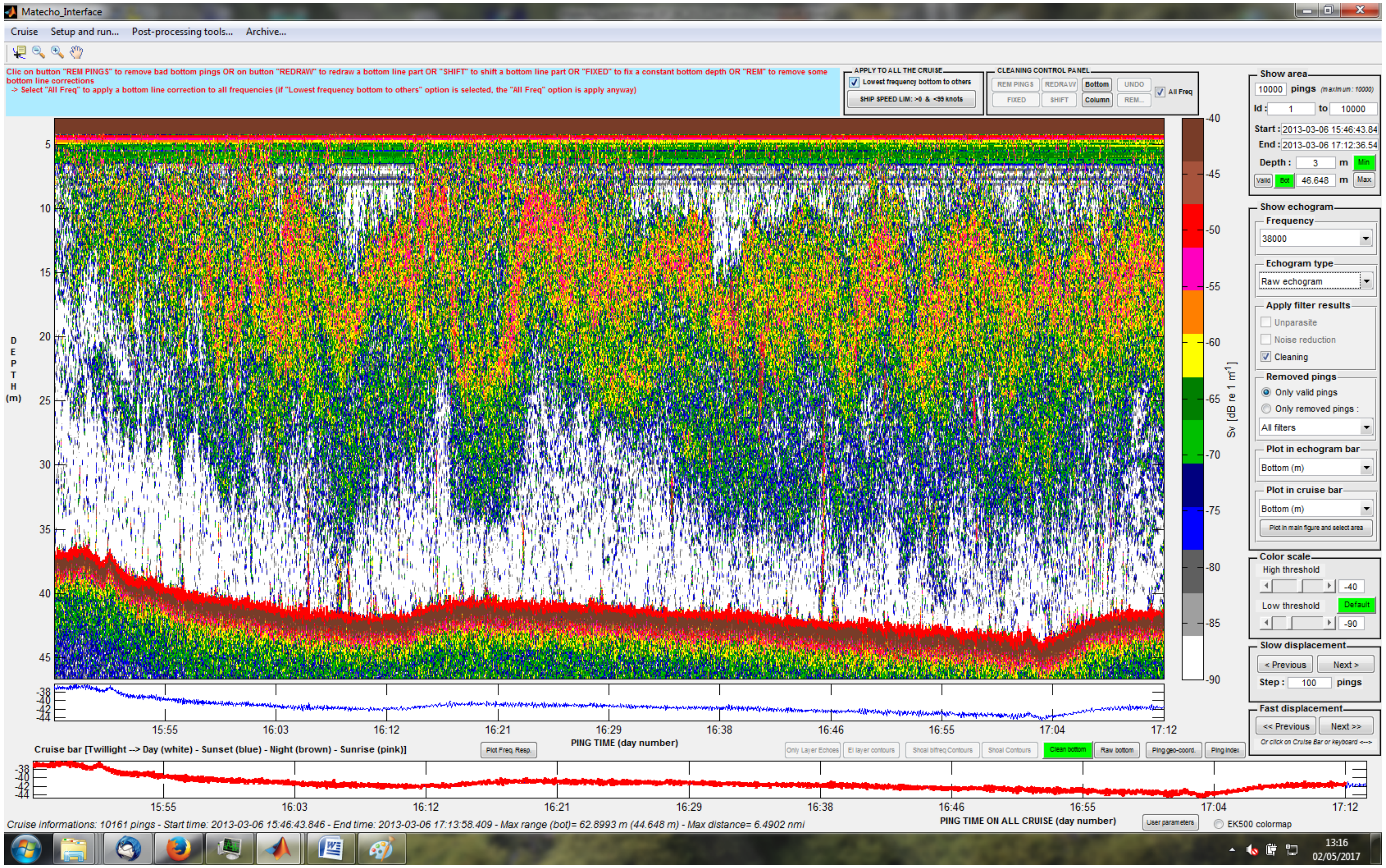




Background and Motivation

Context

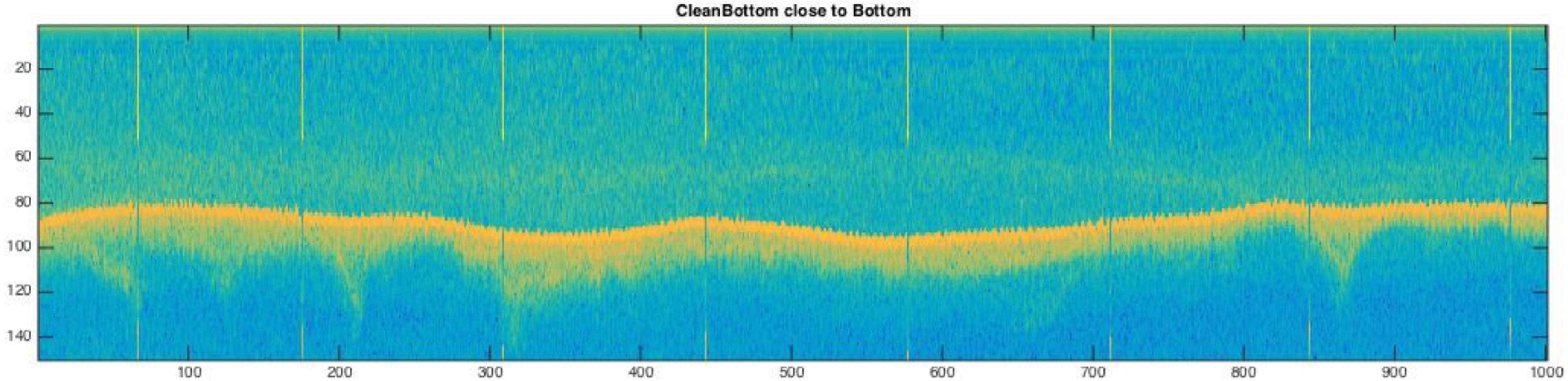
- Stock assessment is important to derive fishery policies to prevent overfishing and protect artisanal fisherman.
- Echo-integration is the main method used for fish stock assessment.
- But before bottom prediction is required

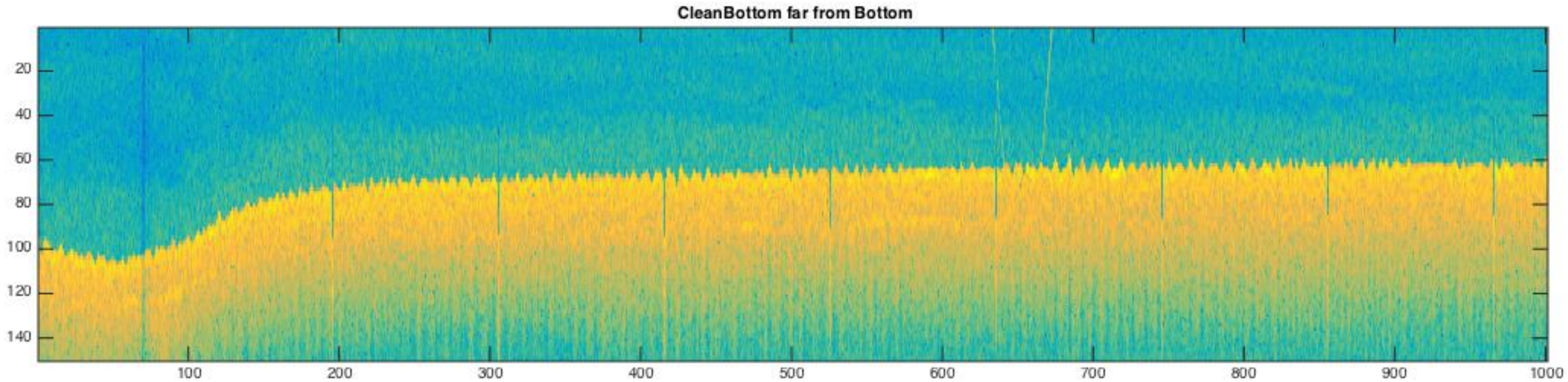


Background and Motivation

Why to Avoid Errors ?

- I**nability to accurately predict the bottom depth** when **high density of fish are present close to the seabed**.
- Indeed, if the **bottom is poorly predicted**, we make **errors in the fish stock assessment.**
- Hence human experts are expected to inspect the whole echogram to correct the bottom depth estimation of the algorithm, and this task is time consuming.





Background and Motivation

Research and Engineering Goal

- Evaluate machine learning (ML) and deep learning (DL) methods on active submarine acoustic data.
- Explore the task of bottom correction as a basic use case.
- Build a simple human assisted system to help the expert correct the bottom from the echogram.

Machine Learning Goal

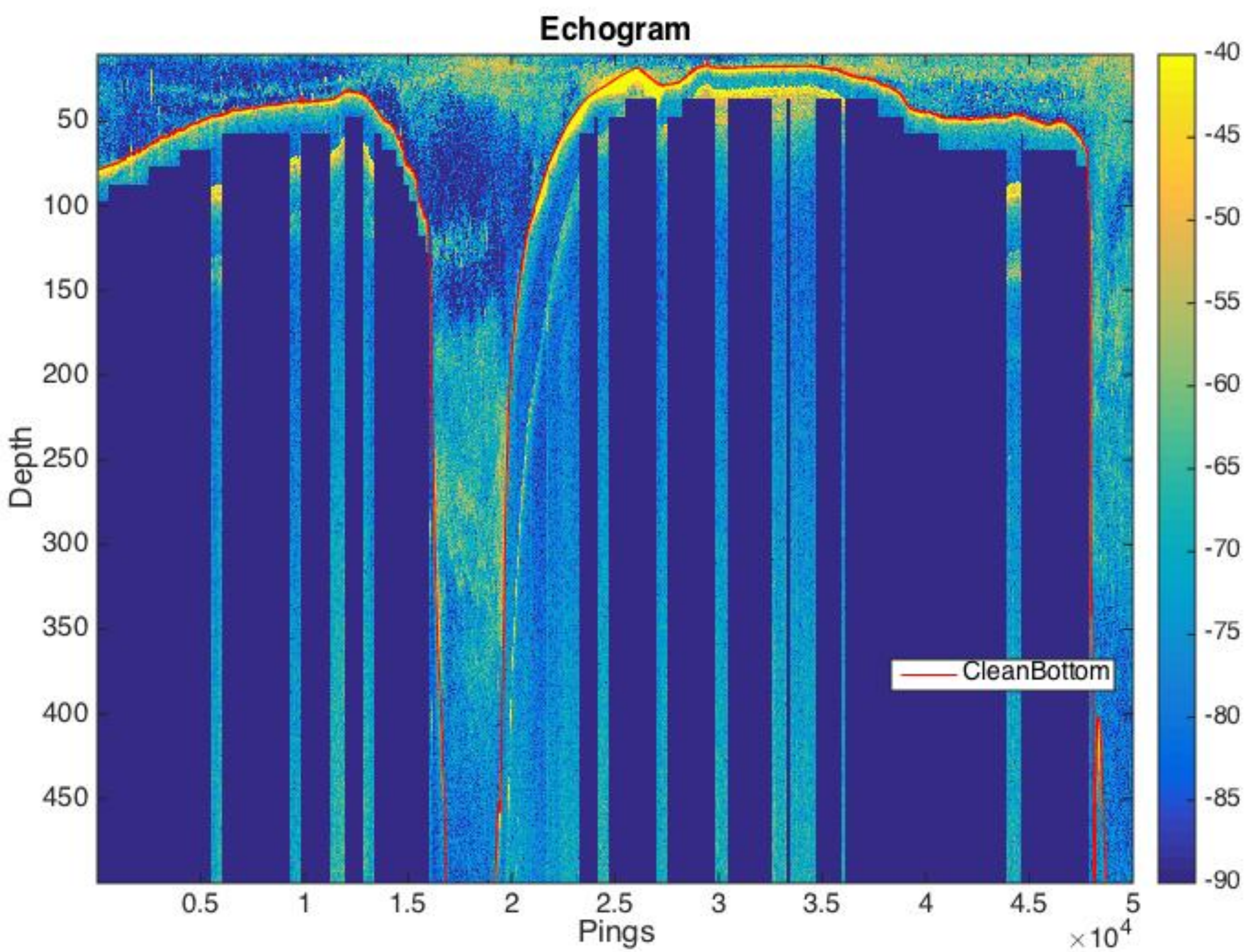
As discussed earlier **the automatic procedure fails when the echogram signal is more diffuse**, thus it requires correction from a human expert. In the following image the upper picture represent a clear echogram and the picture just below represent a diffuse echogram.

- **GOAL:** Classify every ping from the full echogram in **two classes: clear echogram** and **diffuse echogram.**
- **MEASURE OF SUCCESS: Accuracy** of well classified pings.

Methodology

Sample of the echogram

- Gradient of color indicates the intensity of the reflection.
- A **column is a ping.**
- The **stong blue color** represent **Not a number** (**Nan)** due to data collection settings during the campaign.
- There are echogram without bottom as you can see in the picture down below.



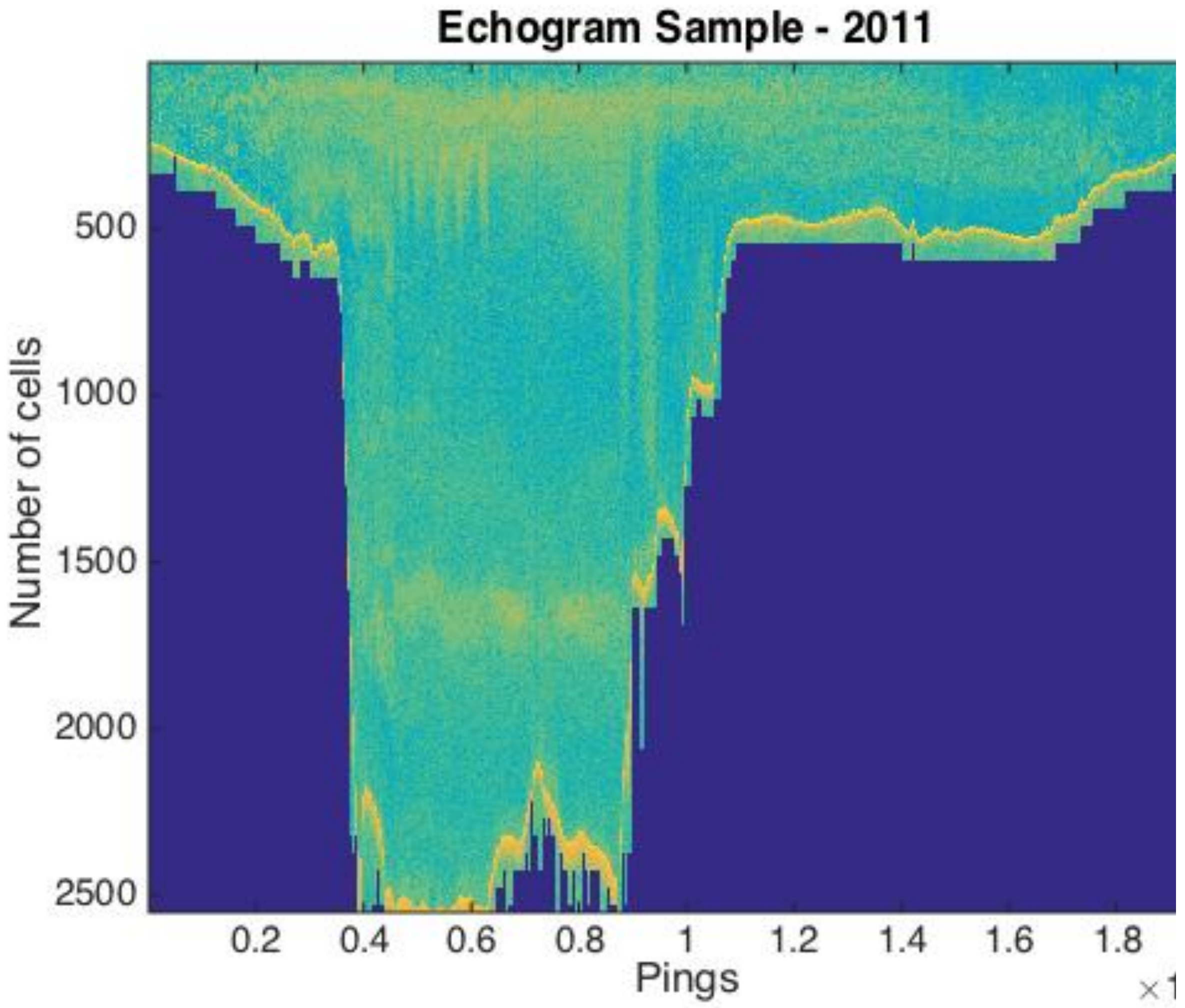
Preprocessing

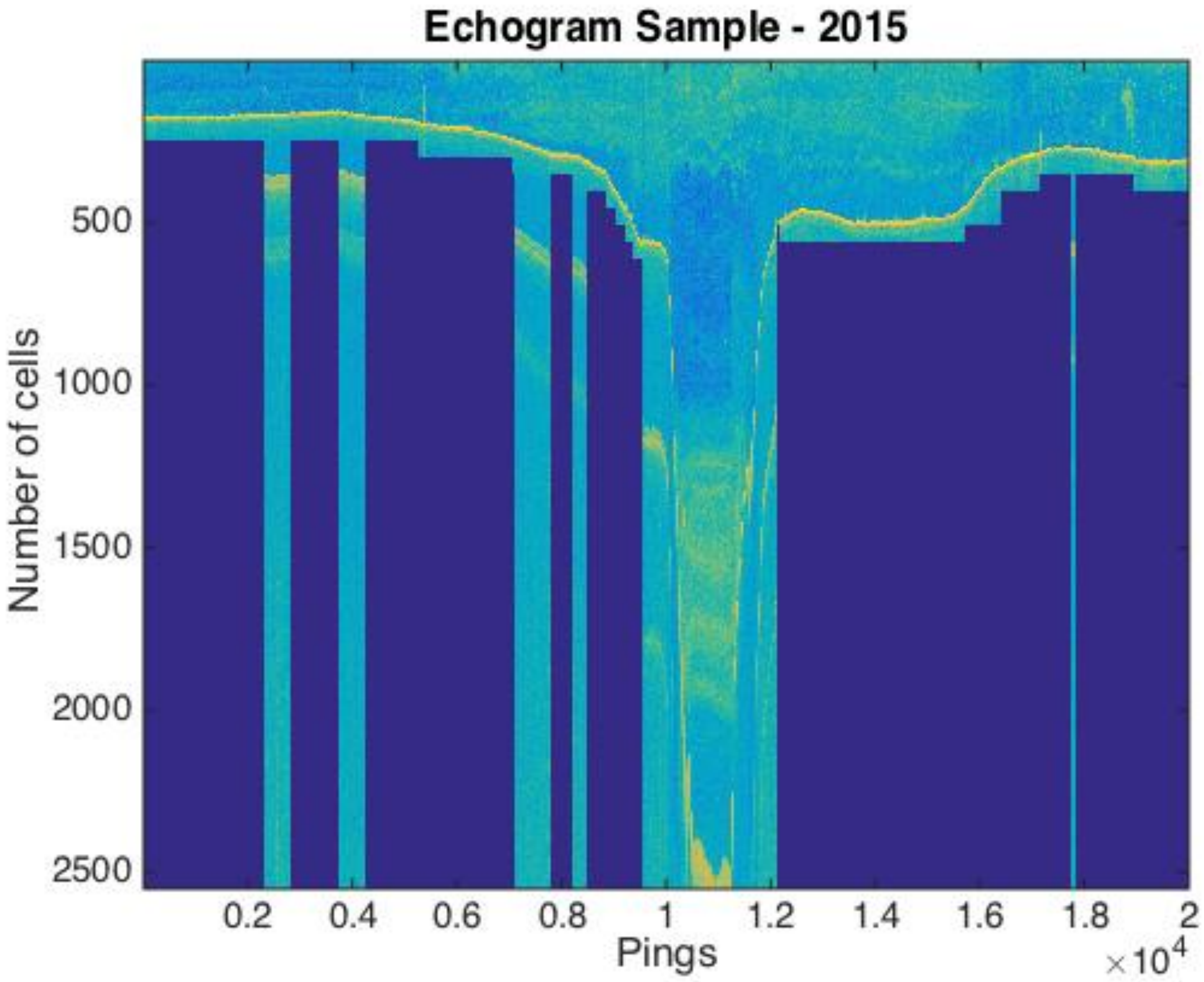
- Remove all the pings with no bottom by selecting only value of echo with a **strong signal** (>-32)**.**
- Replace all Nan by -200

Methodology

Data Format

- Due to difference in data collection settings, the echo from 2011 and 2015 differs,
In particular the **position of Nan with respect to the bottom** differs as we can see below.





- To address this we will make two experiment.

Methodology

Goal

Train a human assisted system to take advantage of past labeled data (2011) that is able to generalize well on mostly unseen data (2015)

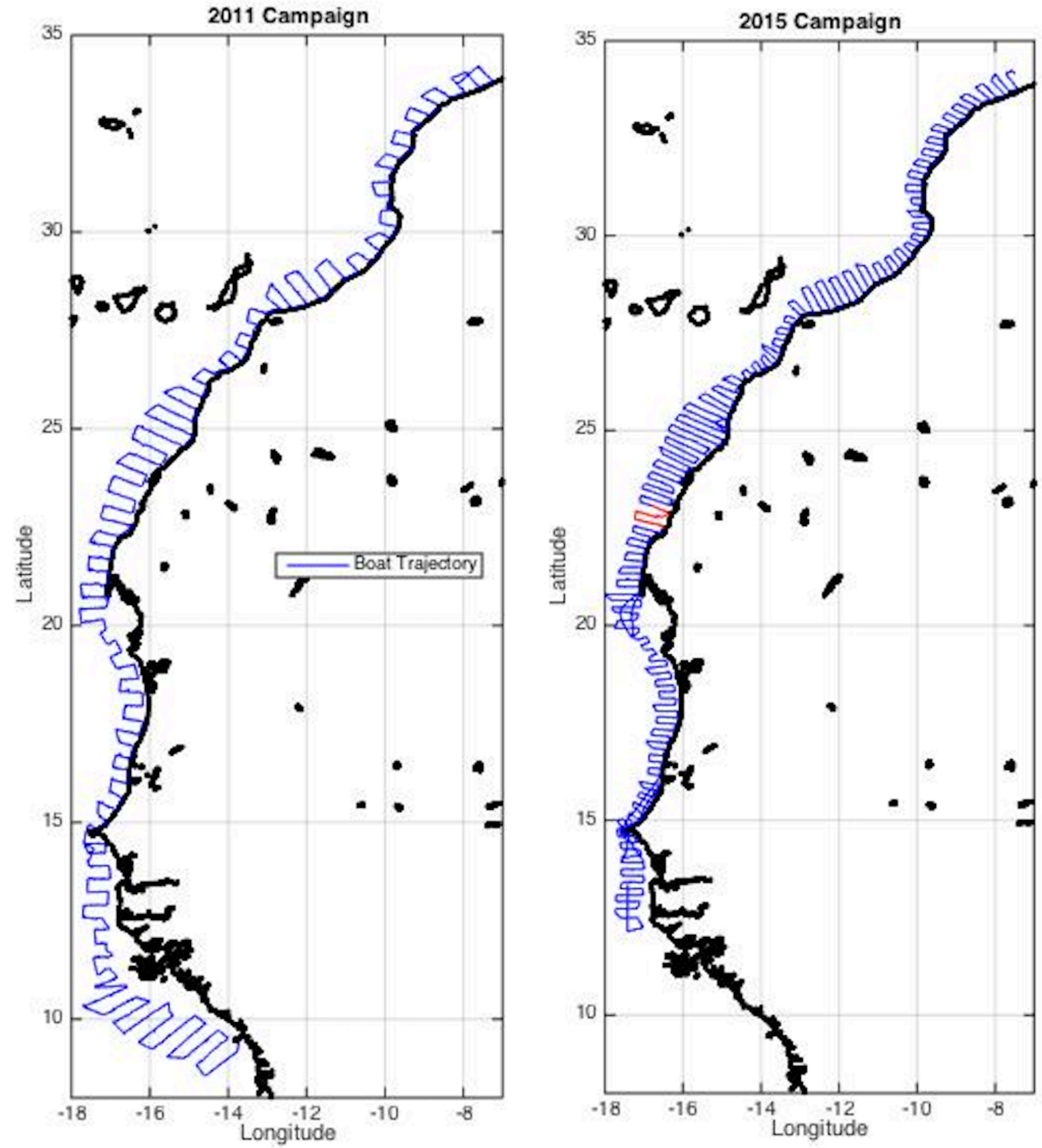
Machine Learning Experiment Design

Experiment 1 - Standard Learning

- Learn with the echogram preprocessed of 2011
- Validate with a subset of the 2015 echogram

Experiment 2 - Cross Domain Learning

- Learn with the full echogram preprocessed of 2011 and a portion of 2015.
- Validate with a subset of the 2015 echogram



Methodology

Reminder About Learning Algorithms

Let's denote

- (X_{train}, Y_{train}) our training set (2011 complete).
- (X_{val}, Y_{val}) our validation set (fraction of 2015).
- (X_{test}, Y_{test}) our test set (2015 complete).
- (x, y) a ping and it's label.

In our case a neural network is a parametric model i.e a function:

$$f_\theta : x \rightarrow P(y = 1|x, \theta)$$

The cost function is

$$l(x, y, f_\theta) = -y \cdot log(f_\theta(x)) + (1 - y) \cdot log(1 - f_\theta(x))$$

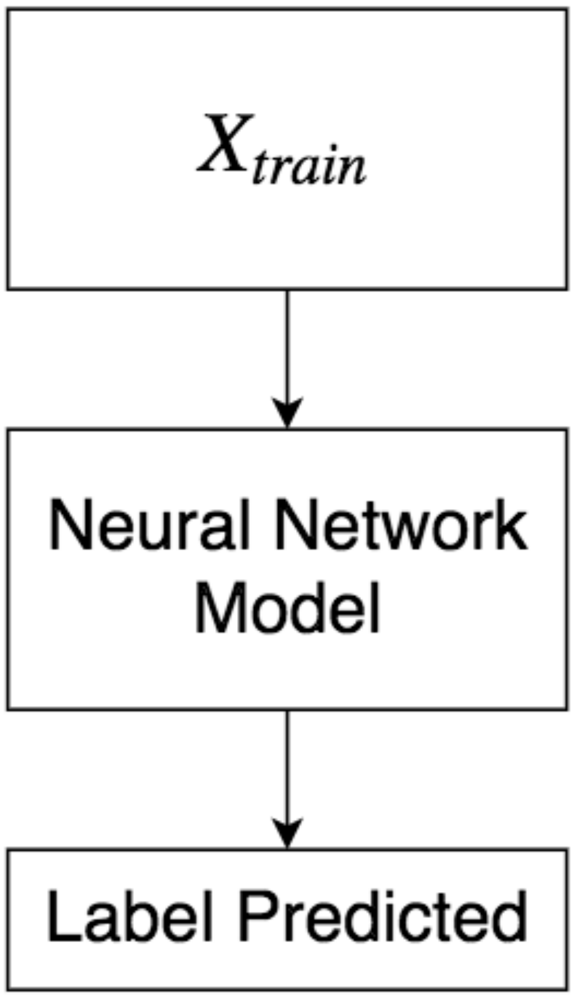
The total loss function is

$$\mathcal{L}(X_{train}, Y_{train}, f_\theta) = -\frac{1}{m_{train}} \cdot \sum_{i=1}^{m_{train}} l(x^{(i)}, y^{(i)}, f_\theta)$$

The learning process consist of minimizing this quantity.

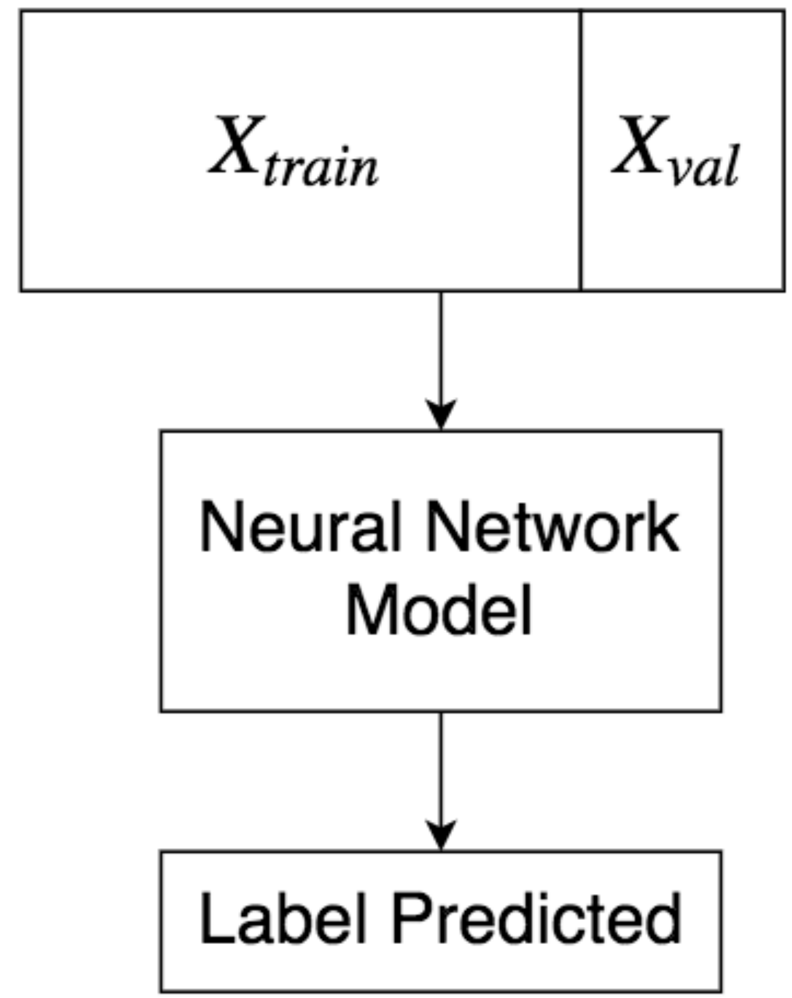
Methodology

Standard Learning

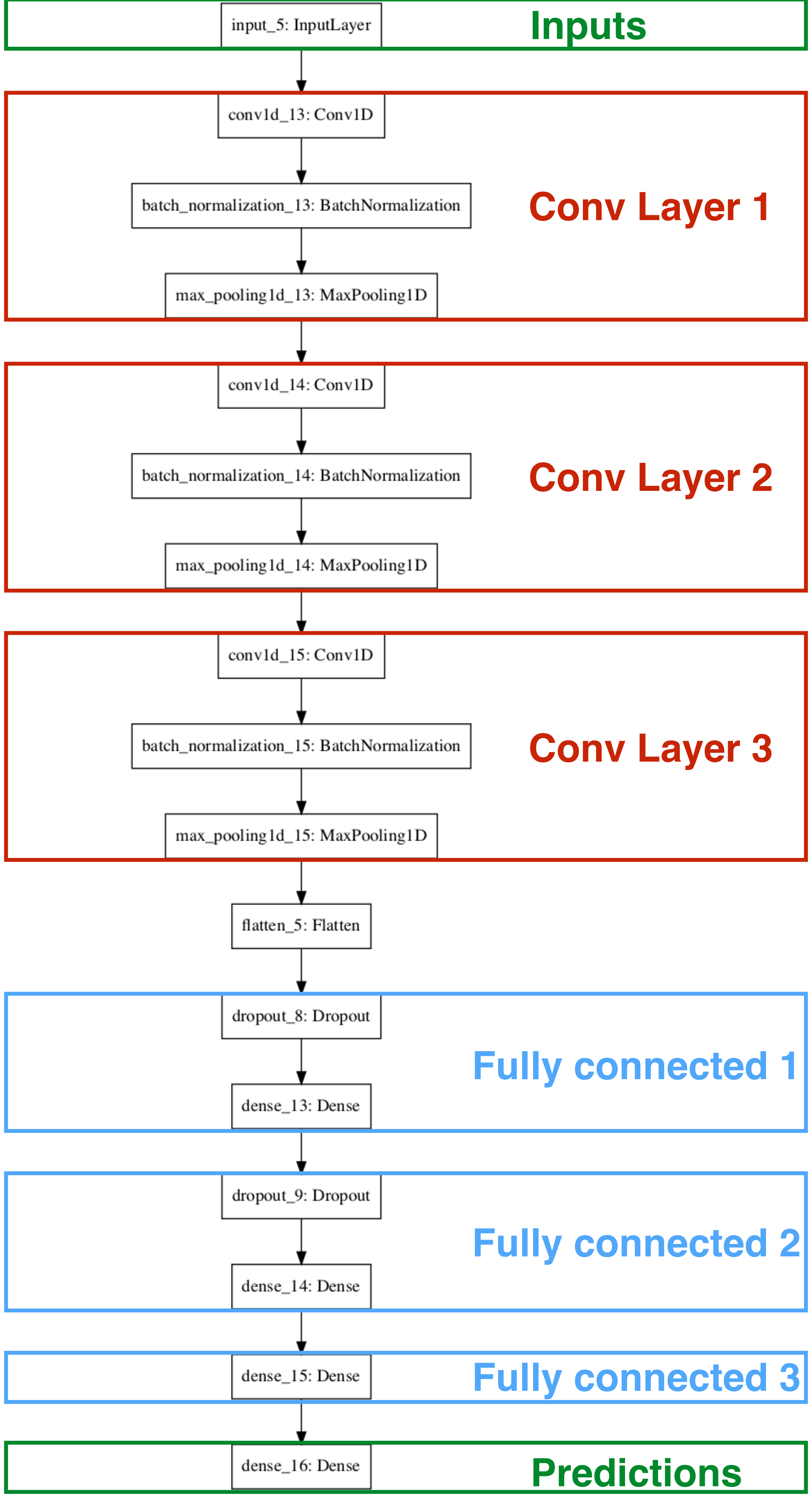


$$\mathcal{L}_1 = -\frac{1}{m_{train}} \cdot \sum_{i=1}^{m_{train}} l(x^{(i)}, y^{(i)}, f_\theta)$$

Cross Domain Learning



$$\mathcal{L}_2 = -\frac{1}{m_{train}} \cdot \sum_{i=1}^{m_{train}} l(x^{(i)}, y^{(i)}, f_\theta) - \frac{\beta}{m_{val}} \cdot \sum_{i=1}^{m_{val}} l(x^{(i)}, y^{(i)}, f_\theta)$$



Methodology

Neural Network Model

We use bayesian optimization to find the hyper parameters

Search space

- kernel1 : [5, 60]
- kernel2 : [5, 60]
- kernel3 : [5, 60]
- no neurone 1 : [5, 600]
- no neuron 2 : [5, 320]
- no neuron 3 : [5, 160]
- dropout 1 : [0, 1]
- dropout 2 : [0, 1]
- dropout 3 : [0, 1]

Hyperparameters

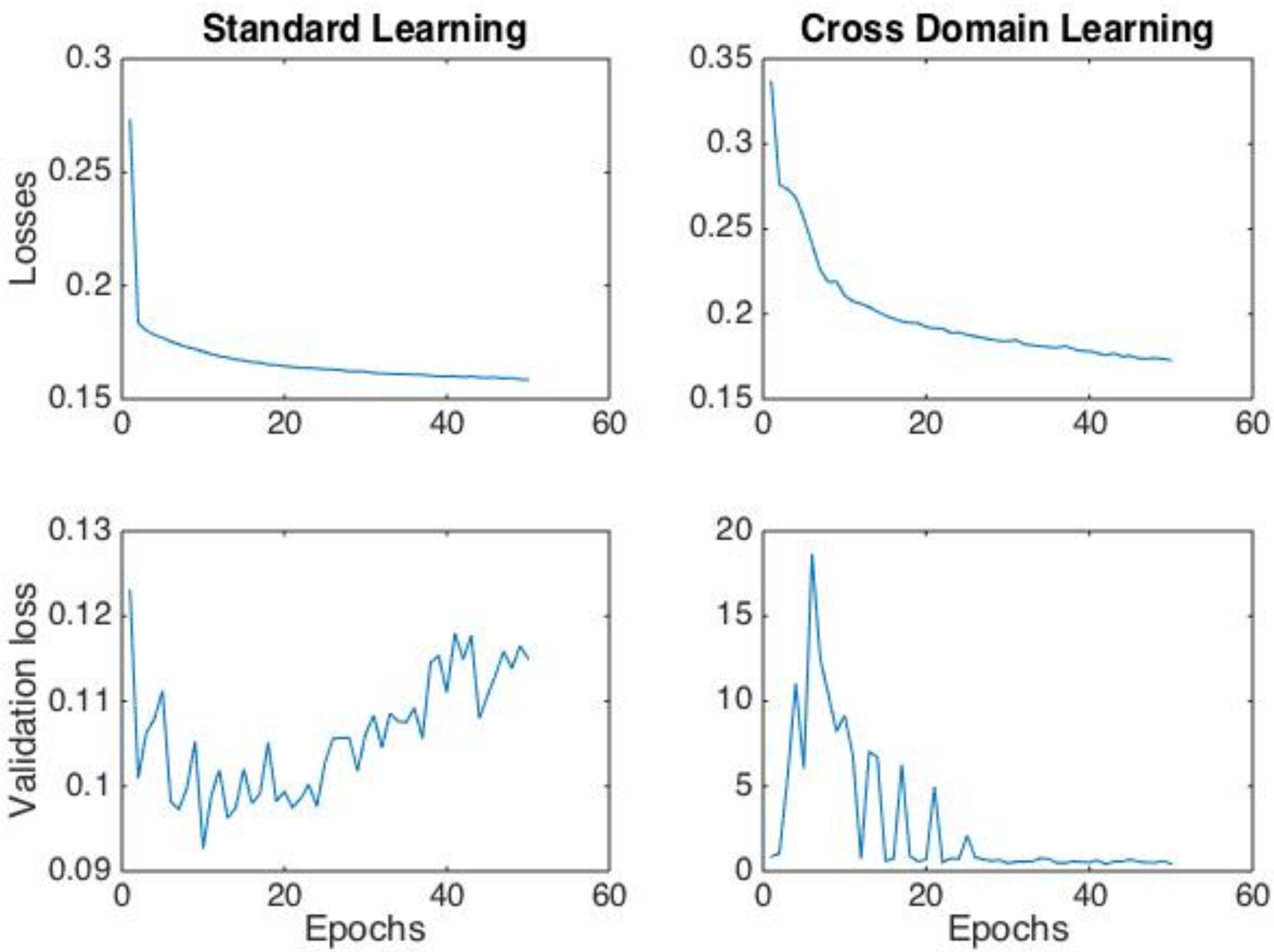
- kernel1 : 56
- kernel2 : 54
- kernel3 : 13
- no neuron 1 : 13
- no neuron 2 : 303
- no neuron 3 : 81
- dropout 1 : 0.5
- dropout 2 : 0.6

Activation function
Selu

Trainable Parameters
400, 539 neurons

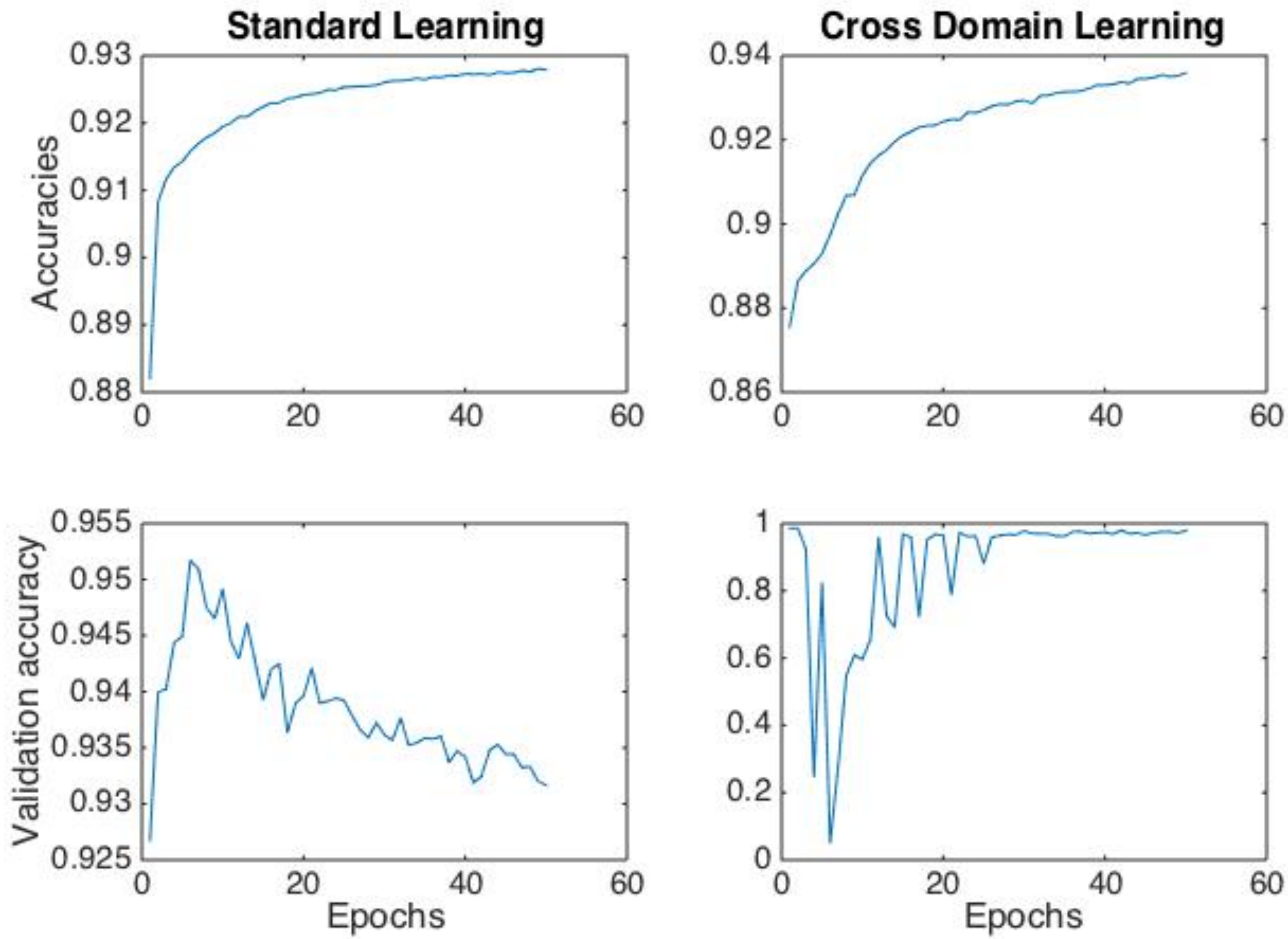
Results

Losses



Results

Accuracies



Results

Results Summary

	2011 Accuracy	2015 Accuracy
Standard NN	93.0%	93.2%
Cross Domain NN	93.1%	**97,8%**

Conclusions

- Machine learning methods specifically neural networks offers good perspective with regards to submarine active acoustic data.
- Those methods are robust to variation due to difference in data collection.
- The model was able to perform at 97.8% on mostly unseen data, thus it can be use as a human assisted system.

Closing Remarks

- The accuracy on the 2015 data set is higher than on the 2011 data set, this is unexpected, and certainly due to less ambiguous examples in 2015
- Also, the training and testing was conducted on the same geographical area, it would be interesting to explore the effectiveness of the model on a new region.

Tools and References

Bibliography

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Tools

- Languages: Python 3, Matlab.
- Python environment: Tensorflow 1.7.
- Critical libraries: Keras, GyOpt, Numpy, Scipy,, h5py .
- GPUs: Tesla K80 on Floydhub.

Merci de votre attention