Neural Networks for the localization of biological and anthropogenic source at a neutrino deep sea telescopes and deep sea observatories

Ludwig Houégnigan, Climent Nadeu,
Mike van der Schaar, Michel André,

Laboratory of Applied Bioacoustics(LAB),
Polytechnic University of Catalonia (UPC), Barcelona Tech

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Outline

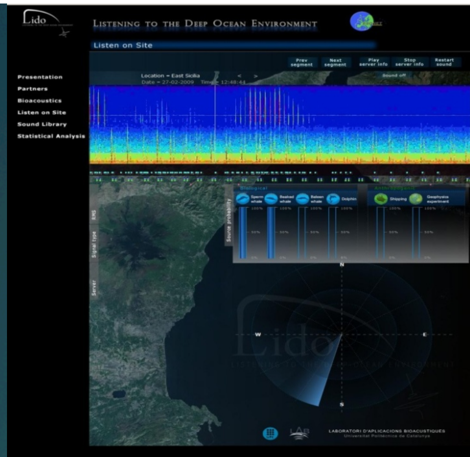
- 1: Context
- 2: From Classification to localization using pattern recognition techniques
- 3: Application to localization at underwater observatories
- 4: Conclusions and perspectives

LIDO (Listening to the Deep Ocean environment)

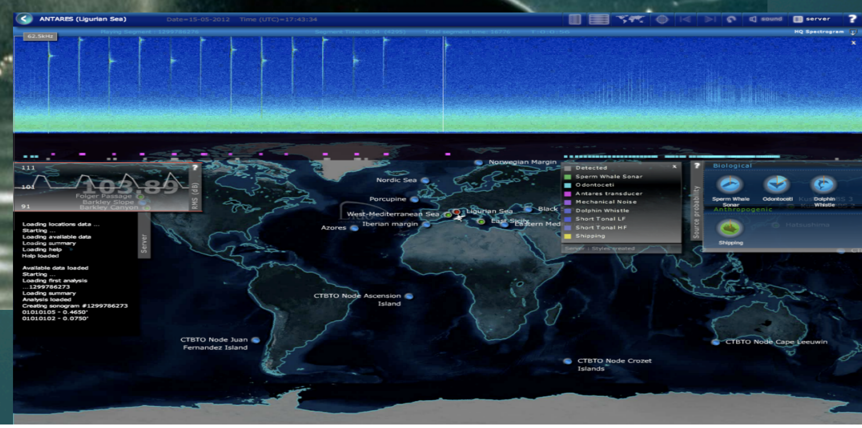
- Effects of anthropogenic noise on marine ecosystems
- Uses cetaceans as bio-indicators for marine ecosystems
- Real-time long-term monitoring of geohazard and ambient noise at sea
- Network of cabled underwater observatories

For more information and live streams, please visit: http://www. listentothedeep.com

ESONET Listening to the Deep-Ocean Environment Lido LISTENING TO THE DEEP-OCEAN ENVIRONMENT



Snapshots of the Lido internet website. Intense biological activity has been detected and is visible on the spectrogram with the presence of sperm whales and beaked whales.



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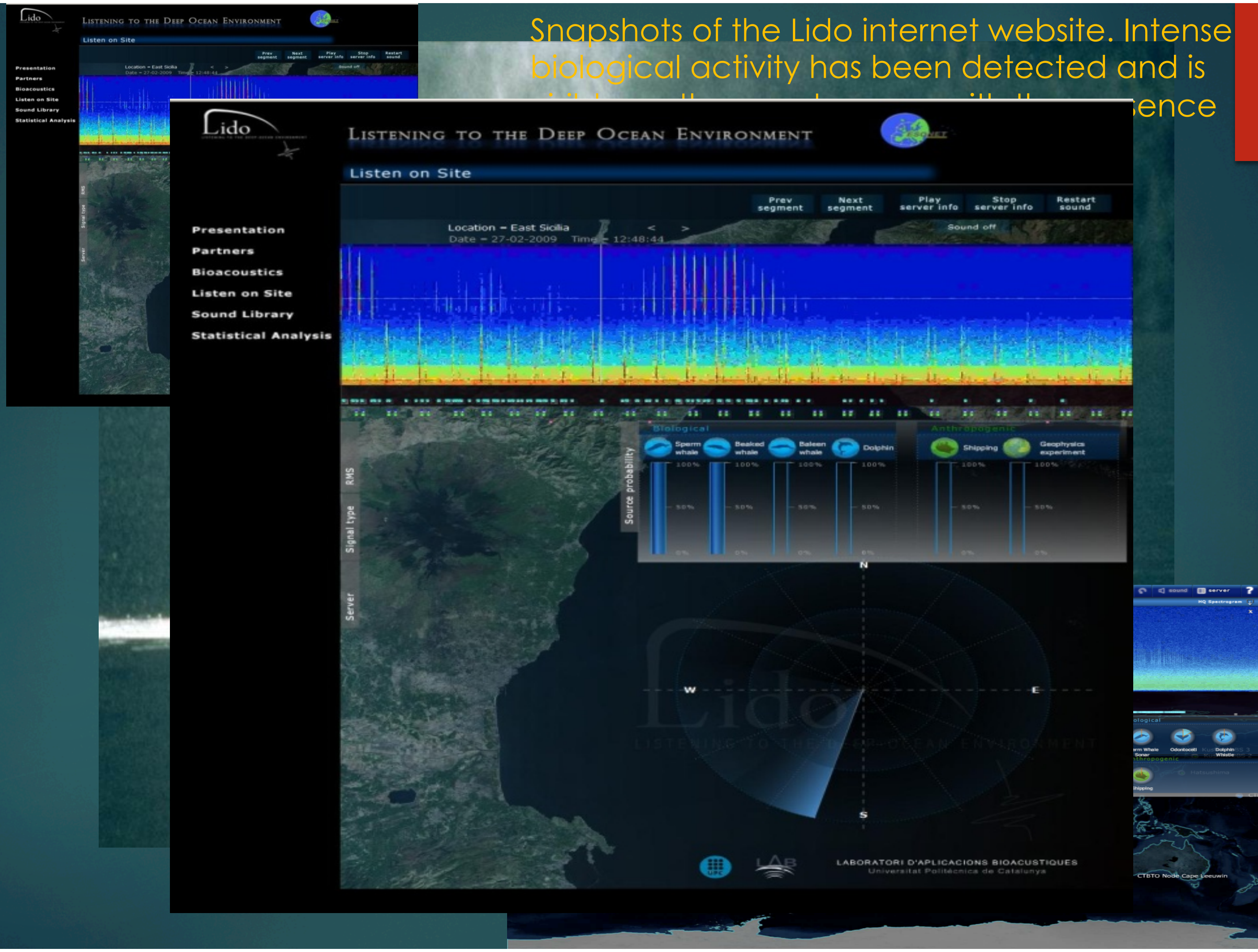

The Evolution of Passive Acoustic Monitoring

- A challenging generation of systems (autonomous buoys, gliders, AUVs, …) has emerged and will be increasingly used for monitoring purposes, so that:

- Software for real-time DCL should be made robust and efficient with regard to data management, energy consumption, payload, etc.

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Comments on previous slides

- New systems for acoustic detection, classification and localization of marine mammals have emerged that include arrays of autonomous buoys, gliders and underwater autonomous vehicles. The LAB has been working on their development and evaluation; they require a thorough optimization of energy and data streams.

- In the meantime localization can be a costly operation. Multiple channels data streams are typically necessary for source localization estimation leading to exponentially increasing computational costs. Some extremely accurate techniques such as beamforming sometimes have to be discarded mostly for computational resources.

- We need to perform as much offline computations as possible so that the online system uses as little energy and computational resources and time as possible. This means that we will train our system to perform source localization offline with real or simulated data. Once trained the system is ready to be placed in a real-time online situation where it will systemically converge to a fast solution with a controlled error. To do this our choice has been to use Artificial Neural networks.

Classification for monitoring

Airgun sound	**Codfish grunt**
Shipping impulses	Sperm whale clicks

Typical tools used for classification come from Pattern Recognition and Machine Learning : Support Vector Machines, Gaussian Mixture Models, Neural Networks…

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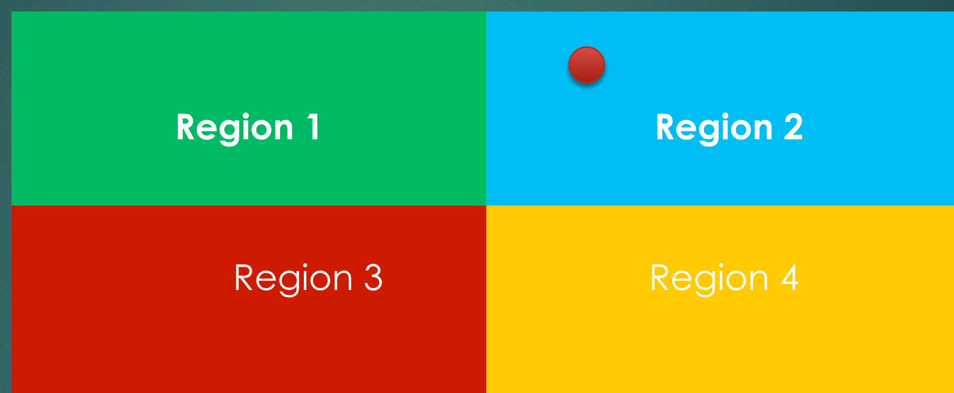
From Classification to Localization



… the same tools can be used here :
Support Vector Machines, Gaussian Mixture Models, Neural Networks…

Localization as spatial classification

In such a situation Neural Networks can be used for a robust localization provided that sufficient and adequate data(features) is provided for training.

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Artificial neural networks

- The human brain is a densely interconnected network of approximately 10^{11} neurons, each connected to, on average, 10^4 others.
- This structure is assumed to give a good account of its abilities to learn patterns and trends in sound, images, time series and all kinds of data…
- Artificial neural networks (ANN) are a machine learning approach that models the human brain and consists of a number of artificial neurons. It aims at imitating- at a much simpler level- the learning abilities of the human brain.

Artificial neural networks
(Application to localization)

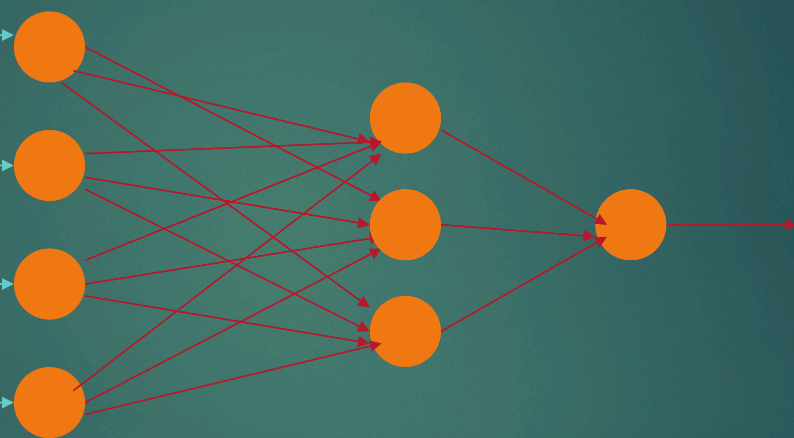
Input :
- Blue whale Vocalization

or

- Sperm whale vocalization

or

- Time-frequency features (phases, time-delays, …)



Output :
Estimated Position of Blue whale, Sperm whale…

Both for classification and localization, neural networks have to go through a learning phase to find adequate weights and biases.

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Artificial neural networks

- Neural network can be used for supervised learning : they aim to minimize the difference between output data and the target data.
- Consists in an Iterative process of adjusting coefficients until user defined threshold on error is reached.

Supervised Learning

Input samples :
- Blue whale sound

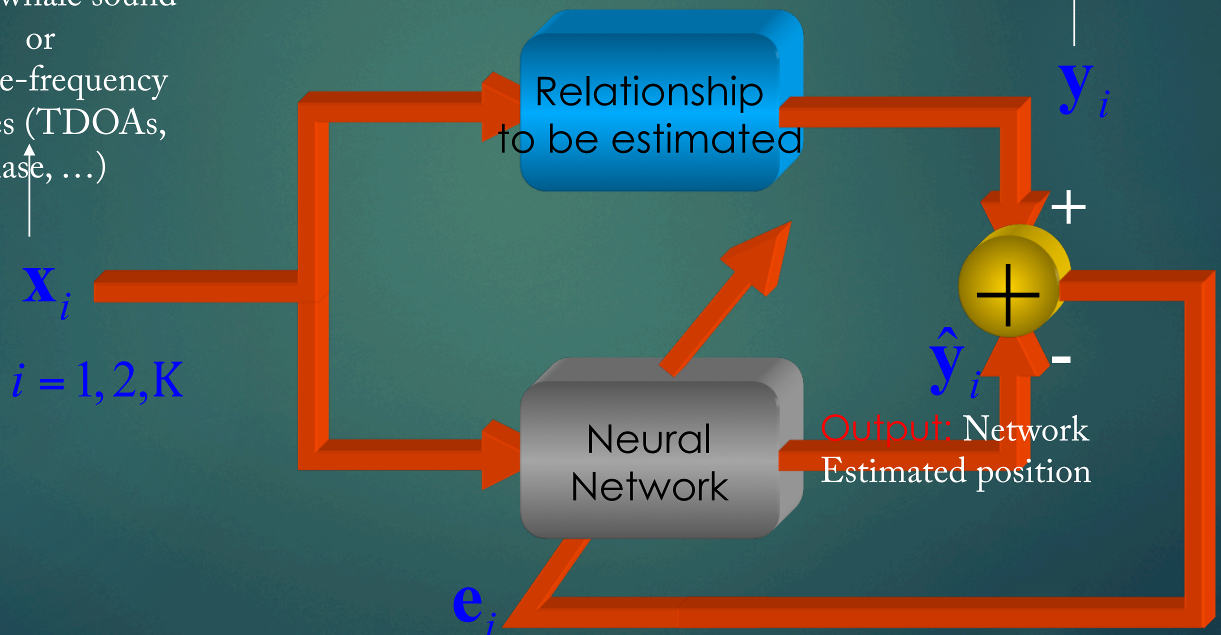
or

- Fin whale sound

or

- Time-frequency features (TDOAs, phase, …)

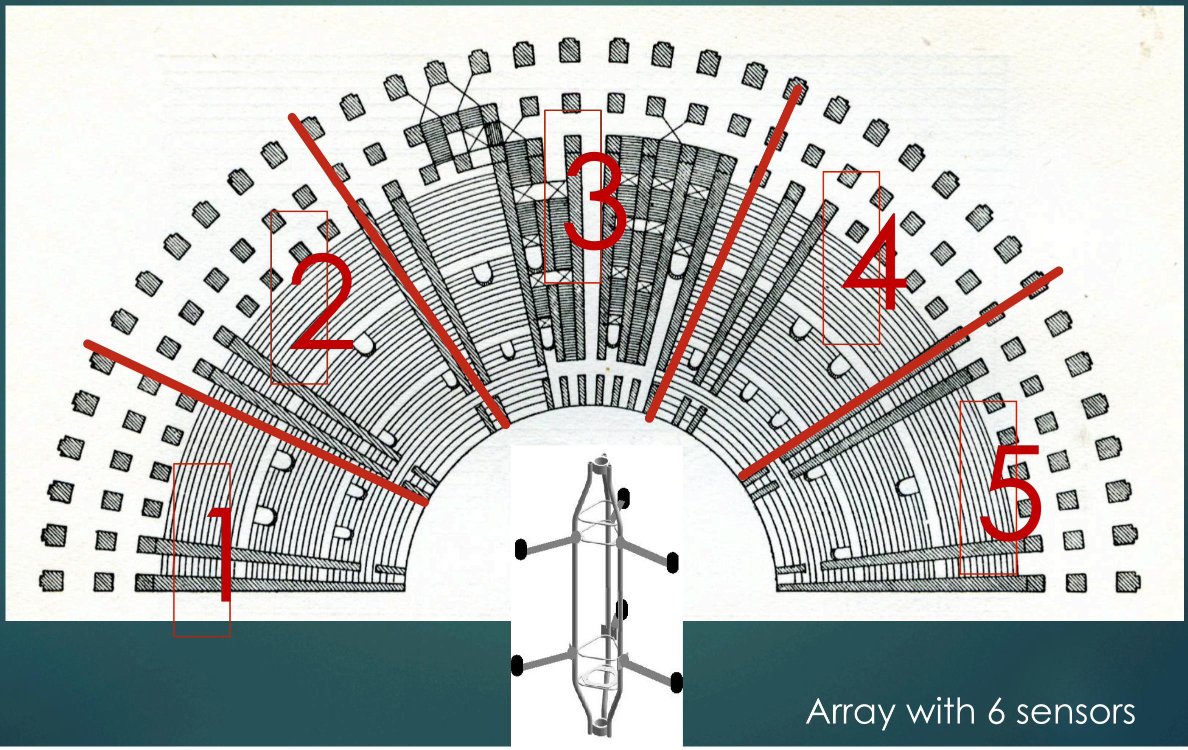
Tutor or target samples: Known position of the source



Difference updates and improves the network

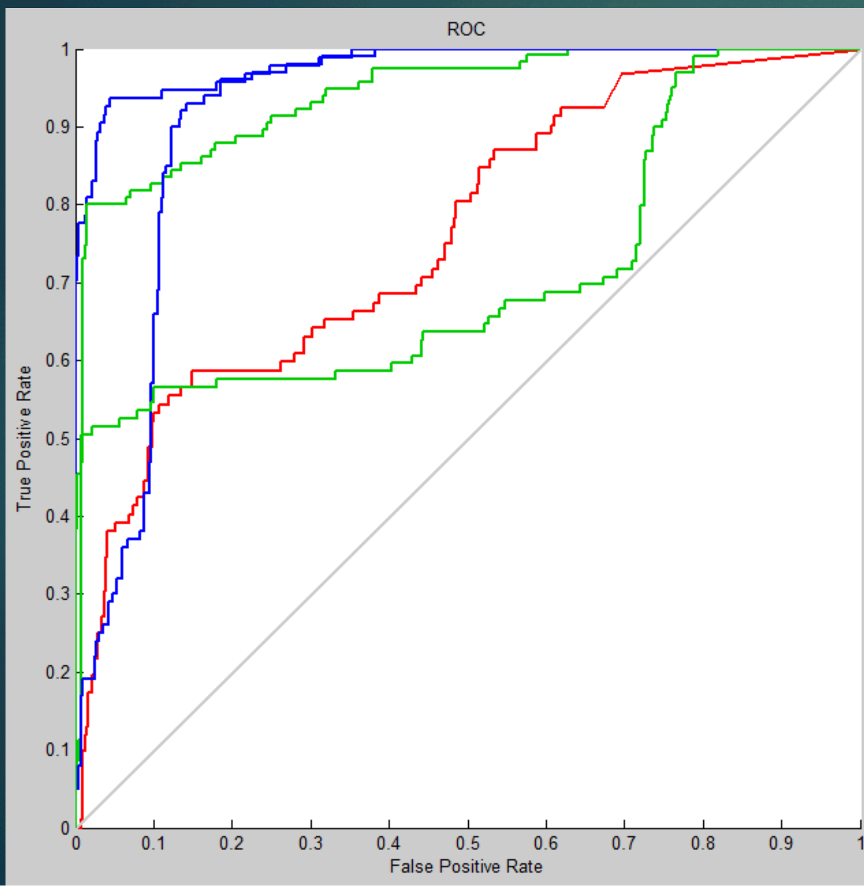
A basic simulation in “this” room…

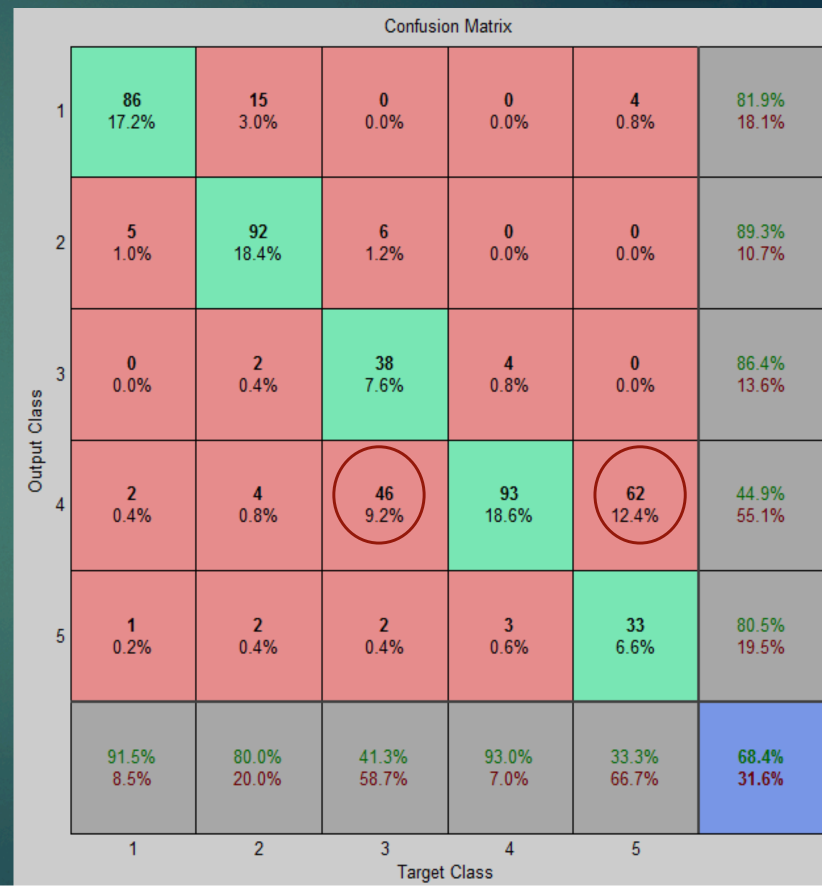
Estimation of direction of speaker in 5 sectors using a neural network



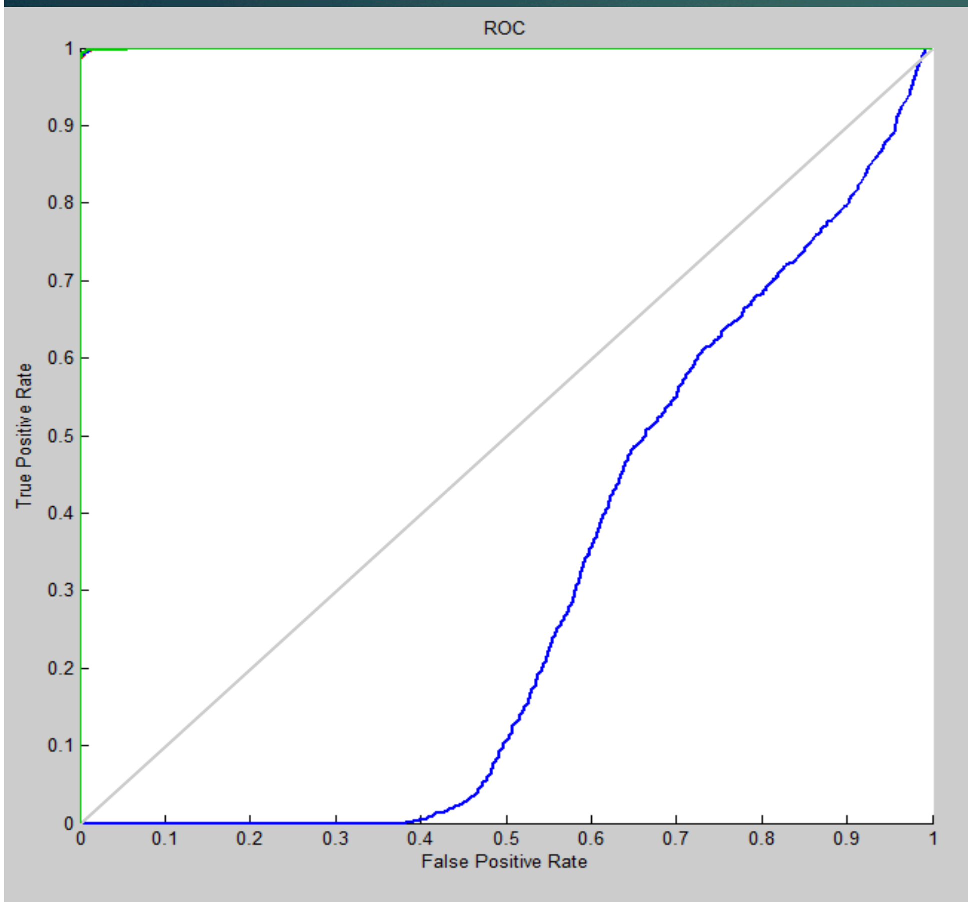
Array with 6 sensors

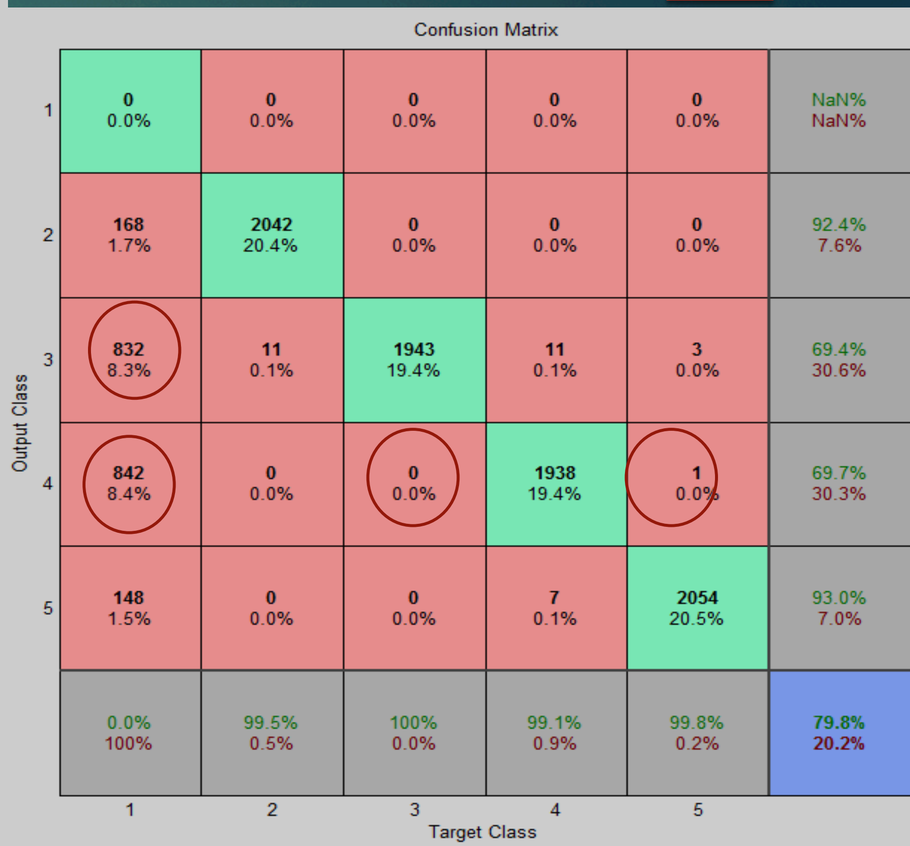
Characterization of localizing neural network
1 layer and 10 neurons has the following performance :
(input=Time-differences of arrival or covariance matrix, target=directions of arrival)





SIZE INCREASE : Neural network with 1 layer and 20 neurons
Change in structure produces improvement in localization…

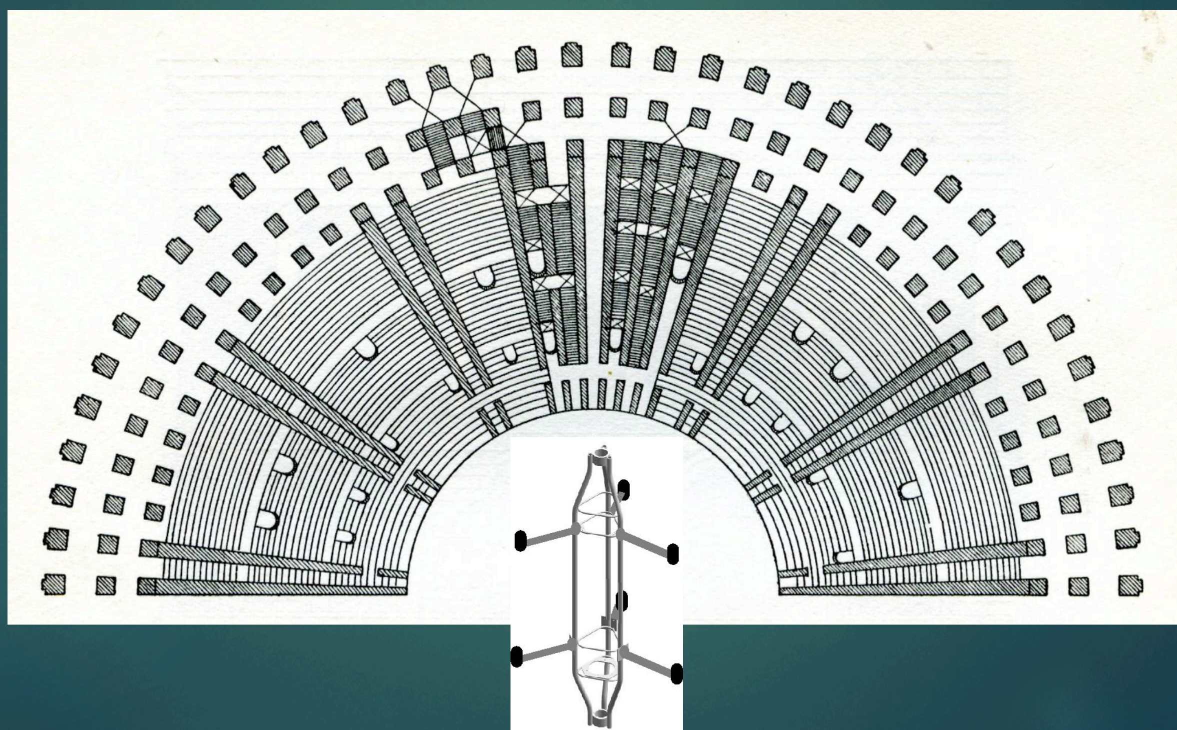




Some metrics of neural network localizer/classifier

	10 neurons	20 neurons
Precision per class	0.9897 0.9502 0.9294 0.9789 0.9792	1.0000 0.9575 0.9783 0.9510 0.9412
Recall per class	0.9580 0.9920 1.0000 0.9300 0.9400	0.9040 0.9920 0.9900 0.9700 0.9600

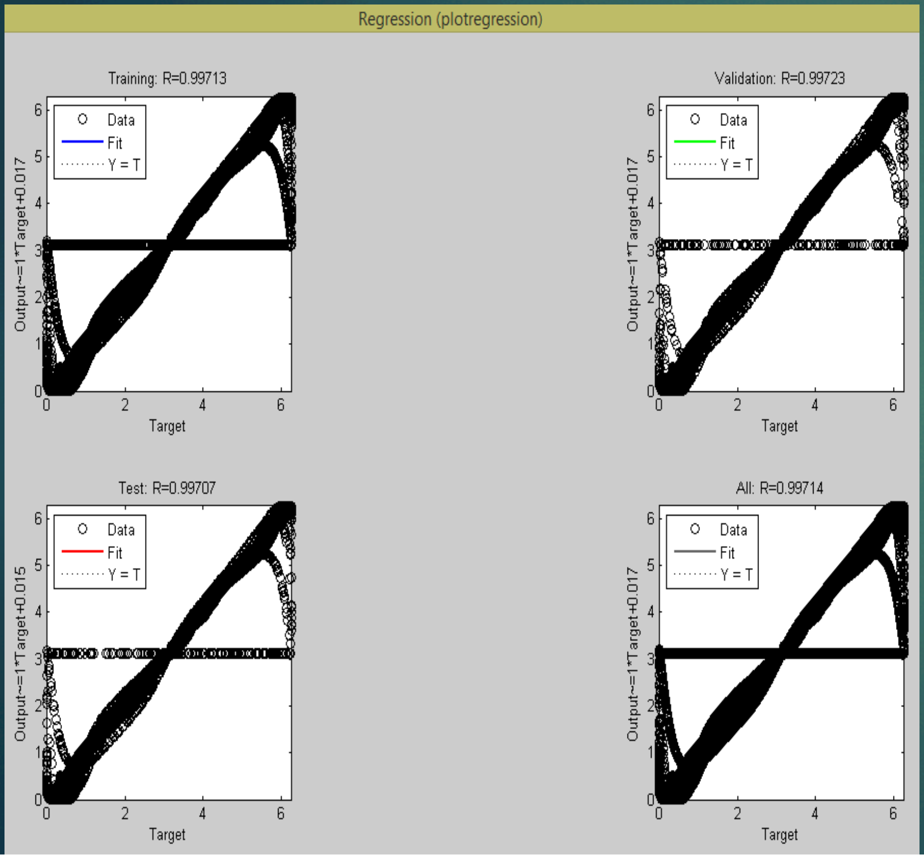
Estimating direction of the source with a resolution of 1 degree (180 sectors) :



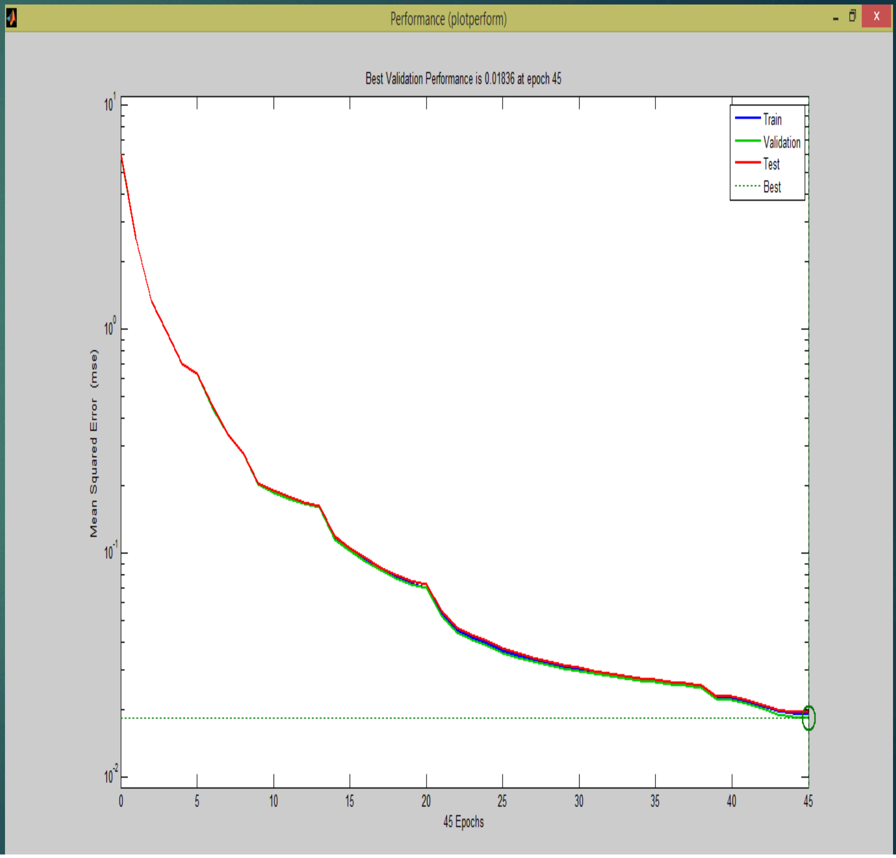
Neural network with 1 layer and 20 neurons

(target angle has resolution of 1 degree)

Regression is good for most angles

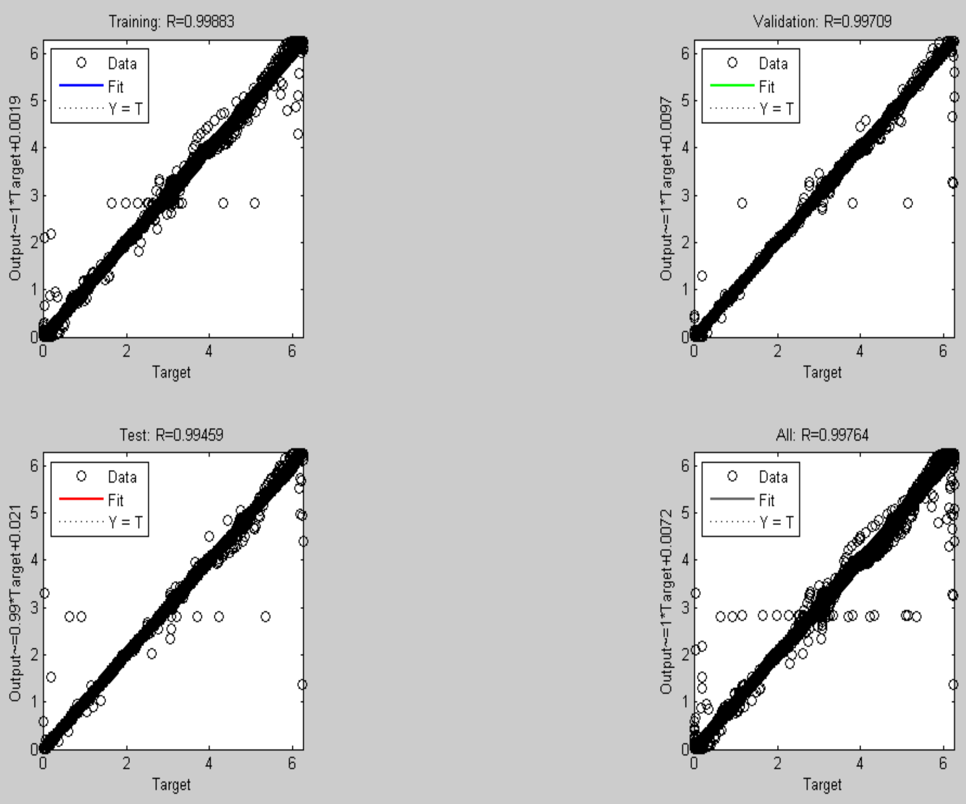


Mean square error goes down to 0.5 degrees

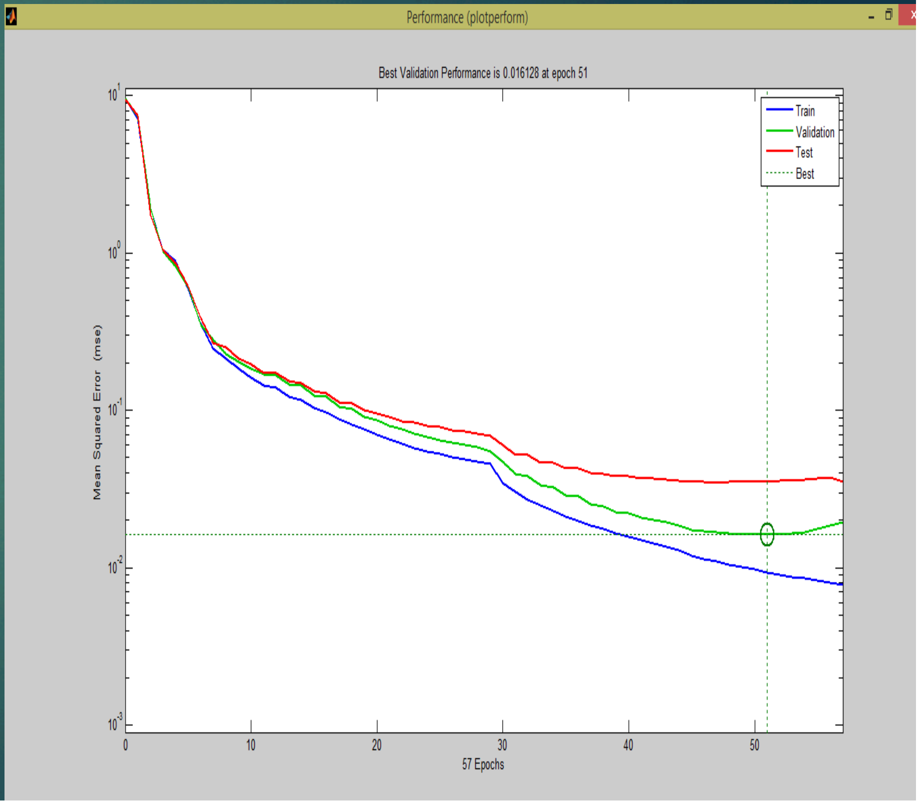


Neural network with 2 hidden layers with 15 and 10 neurons
(target angle has resolution of 1 degree)

Regression is good for most angles….



Mean square error also goes down to 0.5 degrees
Variance is reduced



Main advantages of this approach

- Provides a drastic reduction of complexity for the same precision as ML solutions and approaches the Cramer-Rao lower bound (variance is controlled).
- Can provide a probability density function for the source position.
- The localizer is sharply engineered with similar metrics as in Detection
  ➔ Output's MSE and variance are explicitly engineered_by us and can feed a tracker.
- Avoids complex matrix computations which makes it more suitable for real-time implementations.
- Can take into account variation in sound speed profile, uncertainty in sensor position and time-delay estimation.
- Provides powerful methods for localization with a great ability for modelling and dealing with complex features and trends in data.

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Training for real world situations :

(a) Robustification with varying additive noise : why ?

Time-delay estimates or covariance matrix estimates have variance.
At training, Gaussian noise scaled on the known variance of the time-delay estimator or non-Gaussian noise can be added to the input TDOAs/covariance matrix in order to come closer to a real-world situation.

(b) Robustification with varying sound speed : why ?

Average speed of sound or sound speed profile are not always availableor may vary …

➔ To make the algorithm more robust, the neural network is trained for several speeds of sound.
➔ A single target may relate to several TDOAs which have different speeds of sound. In that case the average speed of sound appears as a latent – yet controlled- variable in the training of the neural network.

Monitoring Applications :

1: Nemo Deep sea telescope
2 : Antares Deep sea telescope

3 : Autec Range (Monaco workshop data)

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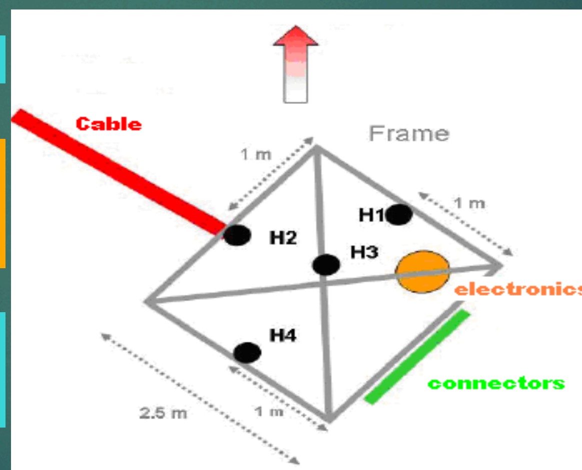
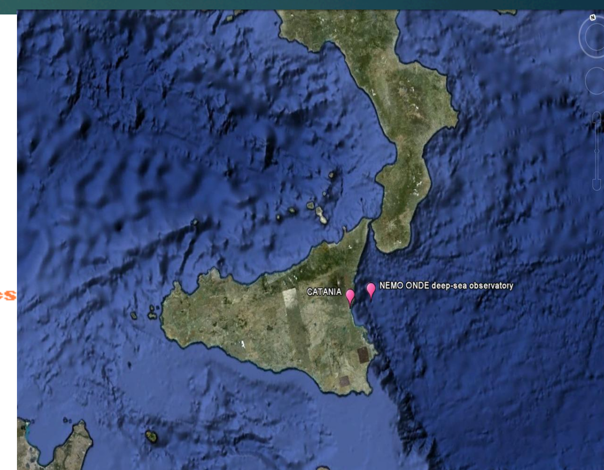
Nemo Deep Sea Observatory (Sicily)
(Neutrino detection)

Objective : acoustic detection of high energy neutrinos

- Array : 4 Hydrophones
- Compact Tetrahedral shape (2.5m side)
- Bottom-mounted, at 2080 m depth

- Bandwidth : 36 Hz - 43 kHz
- Suitable for the monitoring of many cetaceans' vocalizations





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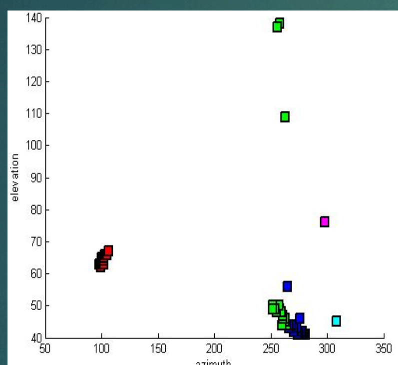
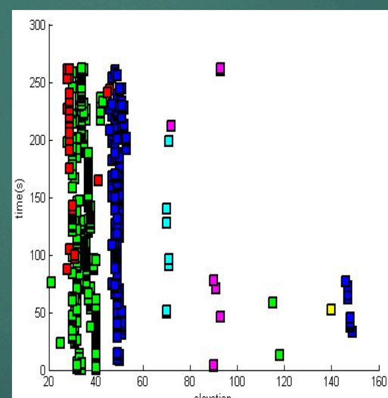
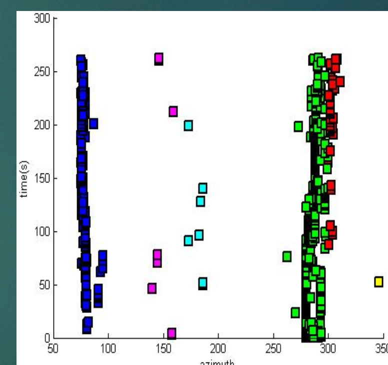
Automated Bearing Estimation, series of click locations

5 minutes recordings, > 600 sperm whale clicks







Elevation vs. azimuth

Elevation vs. time

Azimuth vs. time

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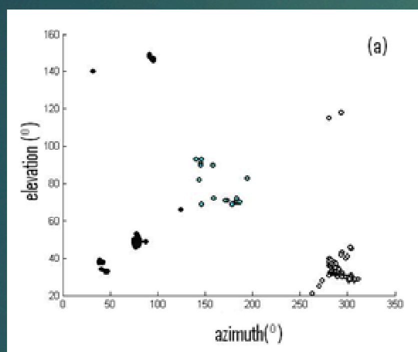
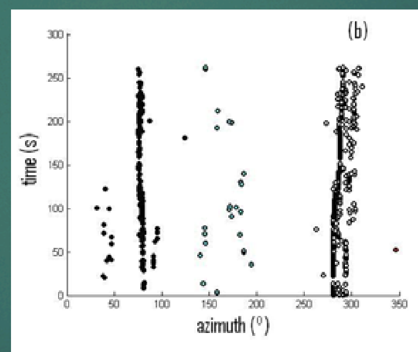
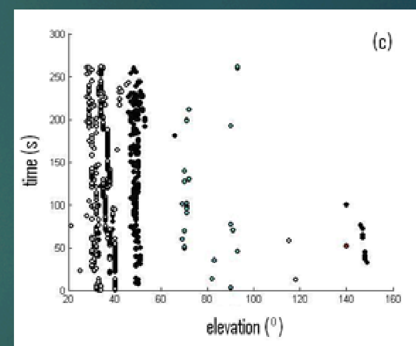
Automated Bearing Estimation, series of click locations

5 minutes recordings, sperm whale clicks







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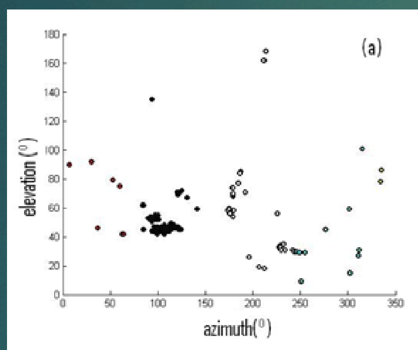
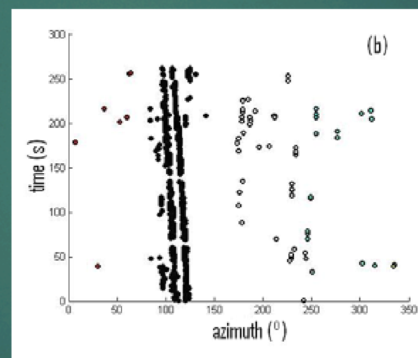
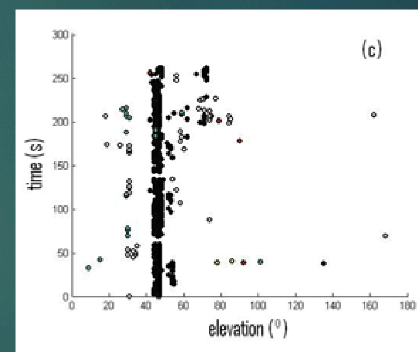
Automated Bearing Estimation, series of click locations

5 minutes recordings, sperm whale clicks







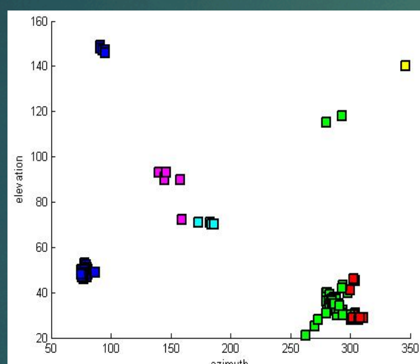
Elevation vs. azimuth

Elevation vs. time

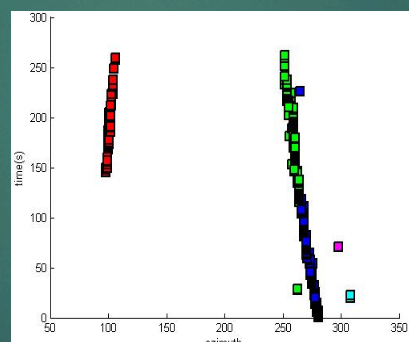
Azimuth vs. time

Automated Bearing Estimation, series of shipping impulses

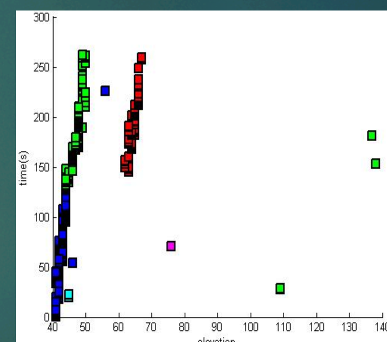
5 minutes recordings, > Shipping impulses



Elevation vs. azimuth



Elevation vs. time



Azimuth vs. time

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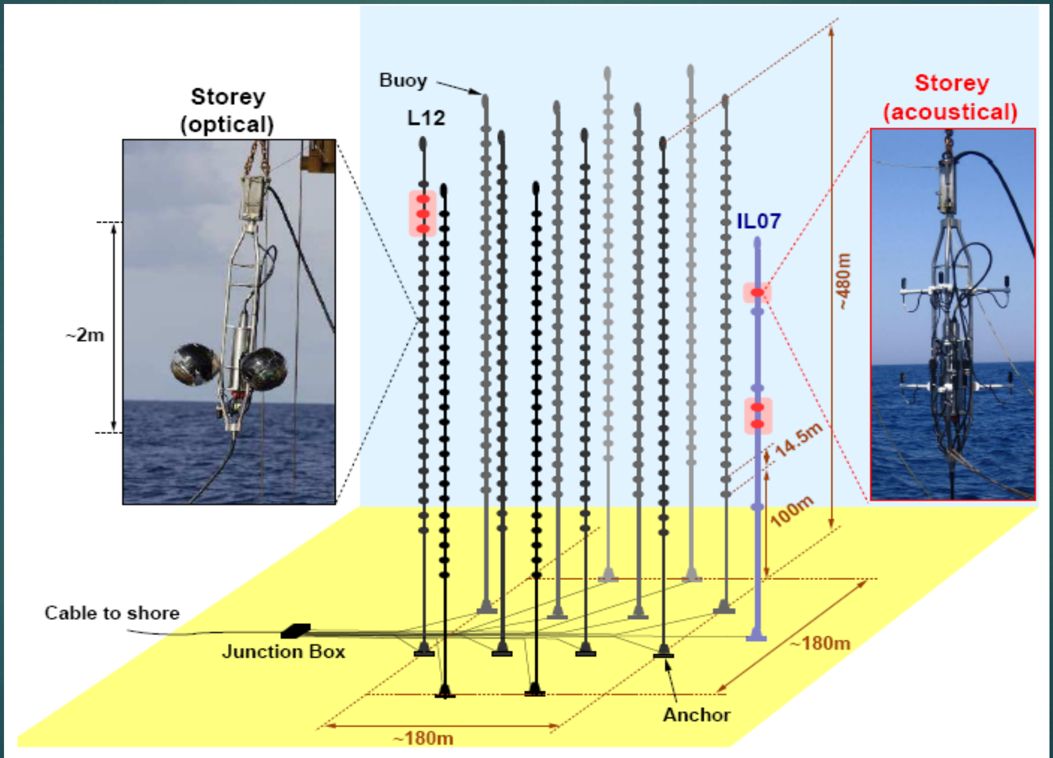
Antares Deep Sea Observatory (Liguarian Sea)
(Neutrino detection)

- > 2000 m depth
- Line/sensor localization
- Pingers
- Source localization



Challenges :

- Saturated signals
- Missing data, e.g. time of emission of pings.
- Real-time

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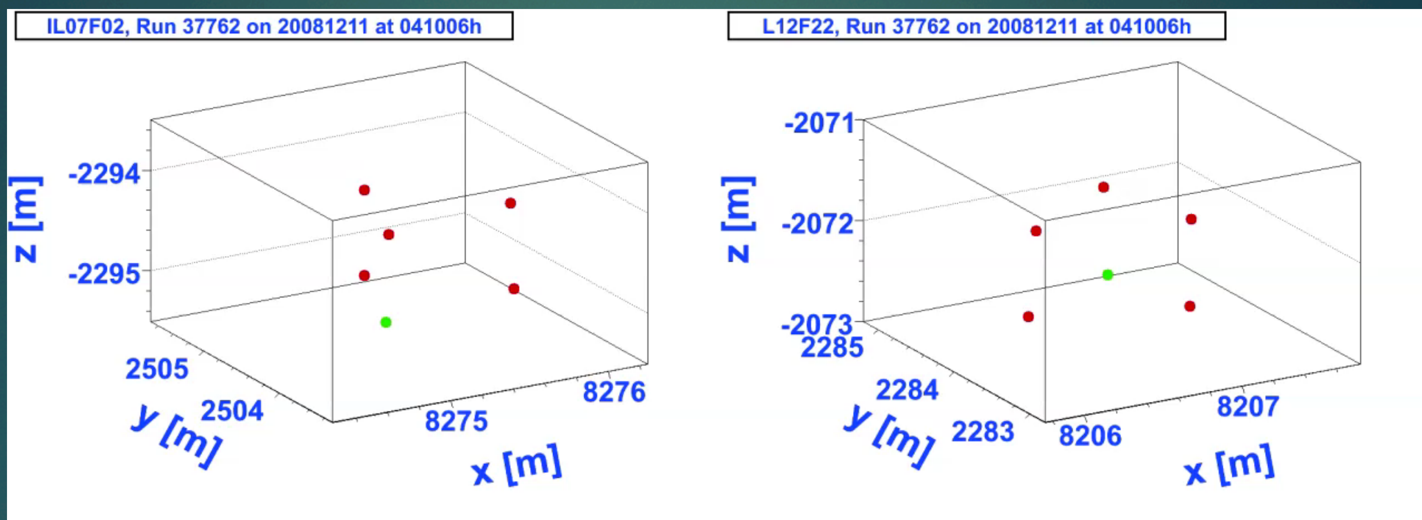
Sensor localization technique



A multilayer perceptron (MLP) with 2 hidden-layers (20 units/10 units) was used to map time-delays for 14 pings and 36 sensors and compared to a more classical minimization approach. No particular effort was made at optimizing the architecture of the network.

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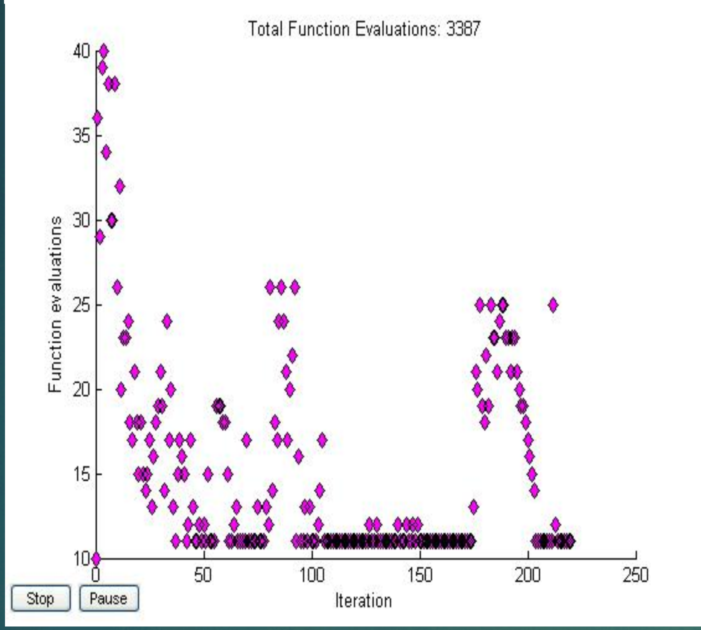
Classical Approach : online minimization	Neural network procedure



1. Create a series of sensors (resp. source) positions with a defined resolution and associated features (TDOAS).
2. Superimpose the features with noise of chosen type (here white gaussian noise).
3. Use the TDOAs and position data from step 1 to train the neural network.
4. Apply trained neural net to estimate position for real data.

- Slow training, 2-3 hours
- Instant convergence (closed-form solution)
- Monitors in real-time the movement of the lines

- Slow process
- Requires differentiable forward model + initial guess.
- Difficult or absence of convergence depending on noise.
- Localization becomes imposible.

➔ **Not wanted for real-time application !**

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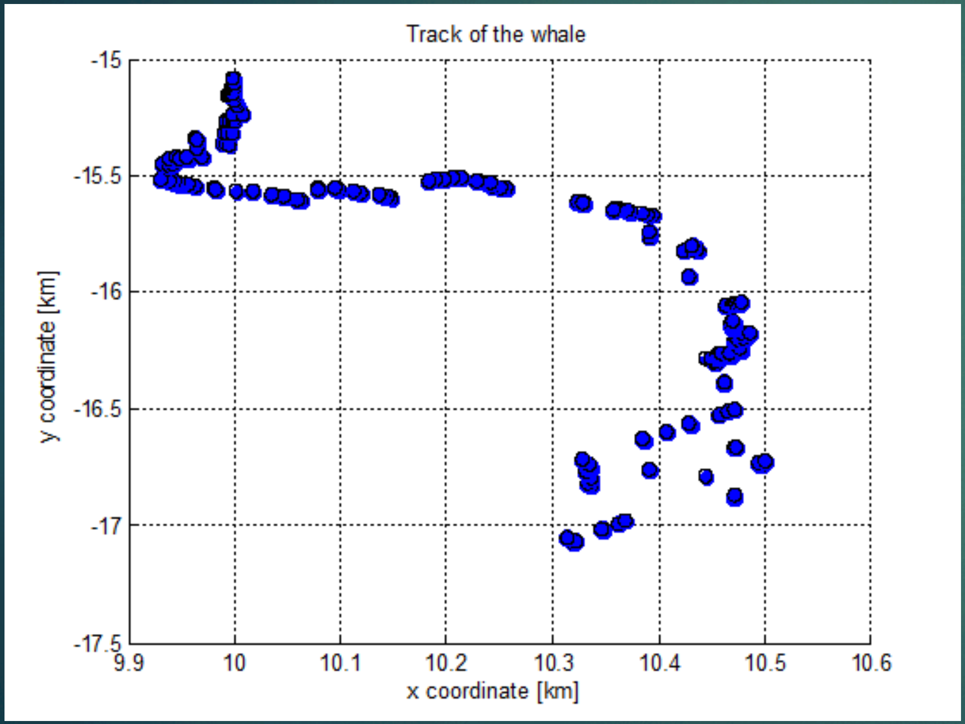
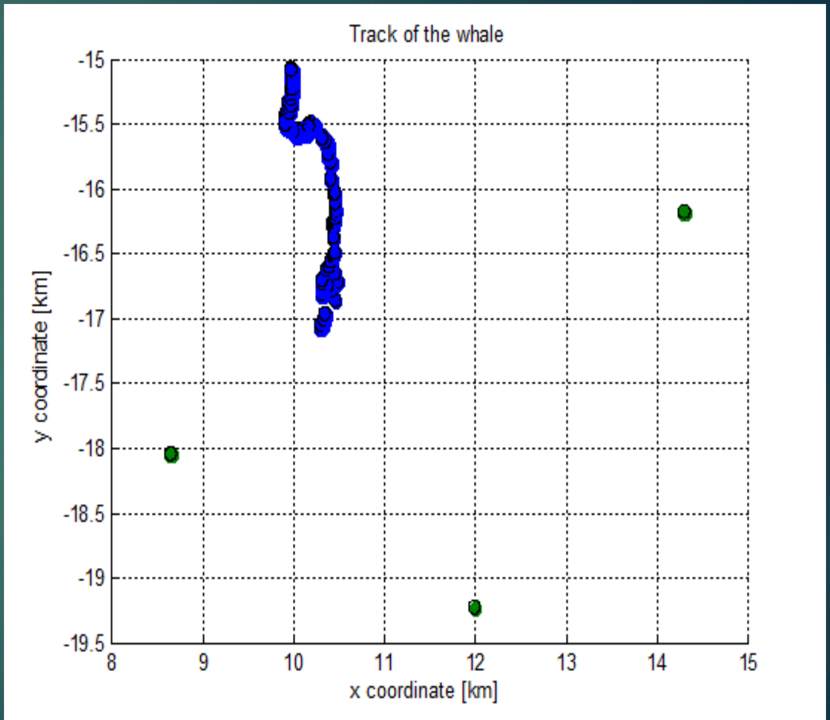
- In the classical approach we go through an error minimization to find the correct line position.
  - Convergence to a minimum can take long.
  - Convergence may fail if data is noisy.
- The neural network always provides a solution with a controlled error in a fixed time.
- The amount of online calculation is minimized by offline training.

Tracking of a sperm whale at Autec Range (Monaco workshop dataset using 3 sensors only)





Conclusions :

- Powerful tools used for classification (SVM, Neural Networks,…) can be used for a robust & real-time localization based on beamforming or TDOAS solutions.

- This automated Localizer can be throughly a priori characterized qualified with the same metrics as DC methods.

- Efficient use of machine learning approach for real-time localization.
- Makes an efficient use of redundant information and all available sensors.

- Suitable solution for gliders, autonomous buoys, catamarans…
- Simple coding => simplified programming tasks before deployment.

- Original training style on high-level features permits to robustify the method and outperforms classic TDOA-based methods and beamformers in noisy environment.

Perspectives and Future Work :

- Increase model complexity (sound speed profile, topography, absorption model) while maintaining real-time duties, e.g. for localization of baleen whales in SOFAR channel (Emulate ray-tracing)

- Approach with larger neural networks (possibly Restricted Boltmann machines , Convolutional Neural Networks and other Deep Learning approaches) :

  - with lower level features
  - Smart room as a proof of concept
    → before extension to more complex deep sea environments
    → taking advantage of large datasets available


Thank you for your attention
… and questions !
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