# Machine Learning Techniques in Acoustical Oceanography

**Μιχάλης Ταρουδάκης** **Κώστας Σμαραγδάκης***

Πανεπιστήμιο Κρήτης Τμήμα Μαθηματικών και Εφαρμοσμένων Μαθηματικών

Ίδρυμα τεχνολογίας και Έρευνας, Ινστιτούτο Υπολογιστικών Μαθηματικών

* επίσης Εθνικό Μετσόβιο Πολυτεχνείο, Σχολή Εφαρμοσμένων Μαθηματικών και Φυσικών Επιστημών

Επιστημονικό Συνέδριο
προς τιμήν του ομότιμου. καθηγητή ΕΜΠ
κ. Γεράσιμου Α. Αθανασούλη:
**ΚΥΜΑΤΑ, ΠΙΘΑΝΟΤΗΤΕΣ ΚΑΙ ΑΝΑΜΝΗΣΕΙΣ**

# Γεράσιμος Α. Αθανασούλης

- Τον γνώρισα στην περίοδο που δούλευα το Διδακτορικό μου (1983-1988)
- Από την αρχή μας συνέδεσε μια βαθειά φιλία
- Με βοήθησε πολύ στη διάρκεια της εκονησης της διατριβής μου και με υποστήριξε με διάφορους τρόπους.
- Συνεργαστήκαμε στα πλαίσια διεθνών και Εθνικών προγραμμάτων.
- Εκτίμησα και εκτιμώ, τον τρόπο σκέψης του, τον αγώνα του για την αριστεία σε όλα τα επίπεδα που αφορούν επιστημονικά αλλά και κοινωνικά ζητήματα.

# Machine Learning in Underwater Acoustics at UoC and FORTH

**Inverse Problems in Acoustical Oceanography**
**(Tomography and Sea-Bed Classification)**

**Use acoustics in active or passive mode**
**(Active or Passive Observatories)**

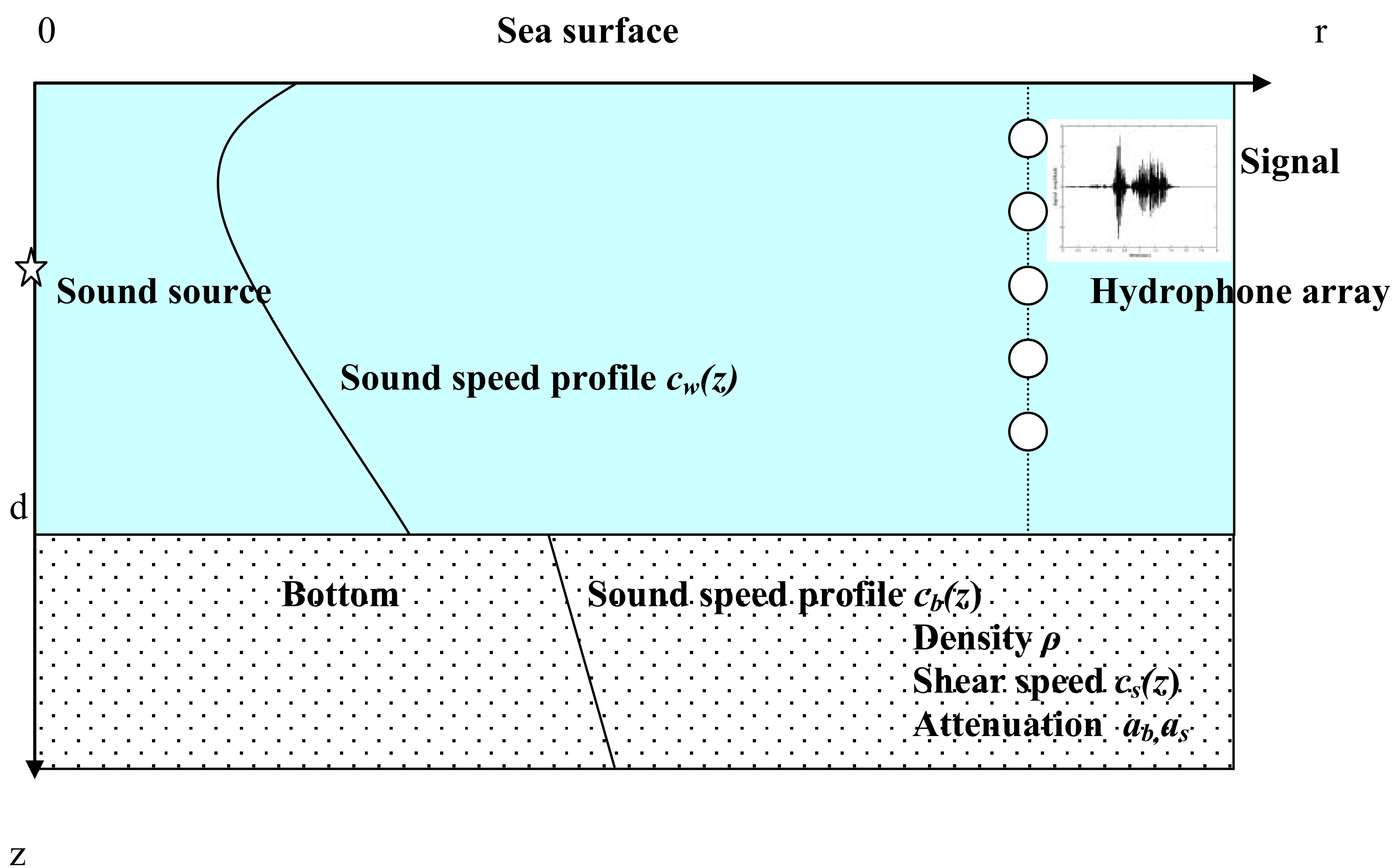
Treatment of an inverse problem of the form

$$\mathbf{f}\left(\mathbf{m},\mathbf{d}\right)=0$$

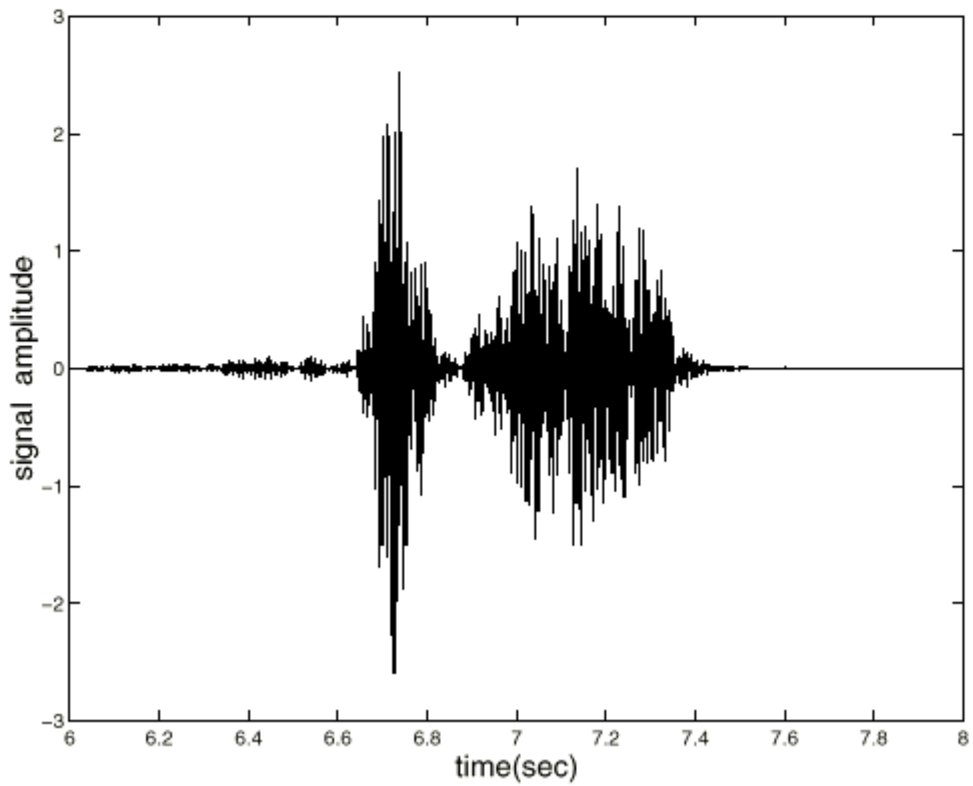
- **m** is the vector of the recoverable parameters and **d** is the vector of observables
- **f** is the model

The parameters **m** describe the environment

# Machine Learning in Underwater Acoustics at UoC and FORTH



# Machine Learning in Underwater Acoustics at UoC and FORTH



# Machine Learning in Underwater Acoustics at UoC and FORTH

- There is a need to define the "observables"
- The observables may be "physical" or "non-physical"
- They form a discrete set of parameters.
- The model describes the way that model parameters and observables are associated to each other.
- Boundary value problem of acoustic wave propagation in the marine environment
- The inverse problem is solved by linear or non-linear methods
- Non linear methods are associated with optimization processes
- Machine learning is involved in both the definition of the observables and the treatment of the optimization process.

# Machine Learning in Underwater Acoustics at UoC and FORTH

**How to obtain the data set d using ML**

- Statistical analysis of the underwater acoustic signals.
- Probabilistic approach (Hidden Markov Models)

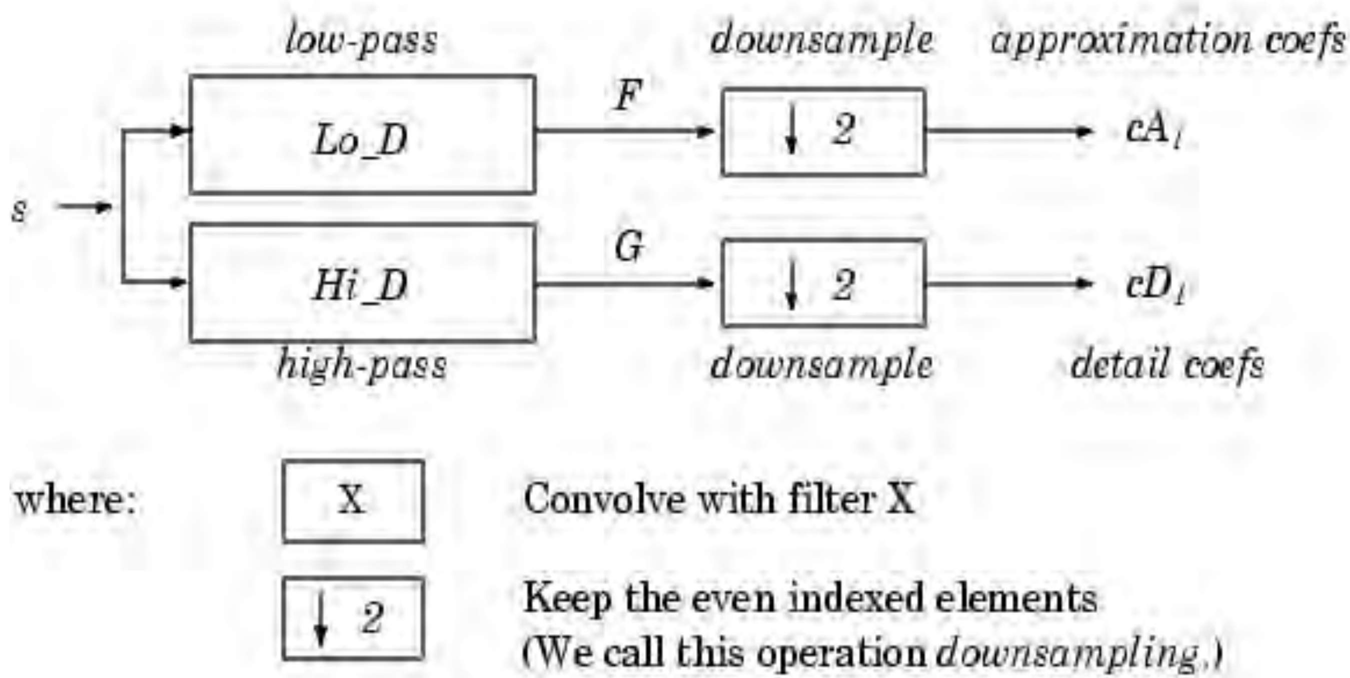
**Inversion Procedure**

- Neural Networks
- Genetic Algorithms

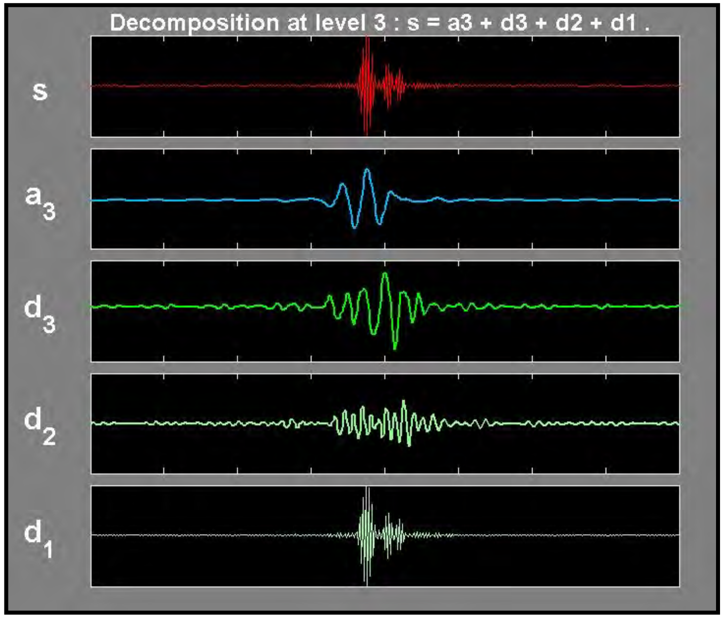
# Statistical characterization of an underwater acoustic signal

- An acoustic signal is decomposed into several scales (levels) through a multi-resolution analysis employing the 1D wavelet transform and high pass and low pass filters.
- The energies of the resulting wavelet coefficients identify the content of the signal at each frequency band scale.
- The statistical characterization is based on the accurate modeling of the tails of the marginal distribution of the wavelet coefficients at each sub-band.
- The wavelet sub-band coefficients in various scales are modeled as *random* variables obeying a symmetric A-stable distribution.

# Statistical characterization of an underwater acoustic signal



# Statistical characterization of an underwater acoustic signal




***Input Signal : s***

$$\phi(\omega) = e^{j\delta\omega - \gamma|\omega|^{\alpha}}, \delta = 0$$

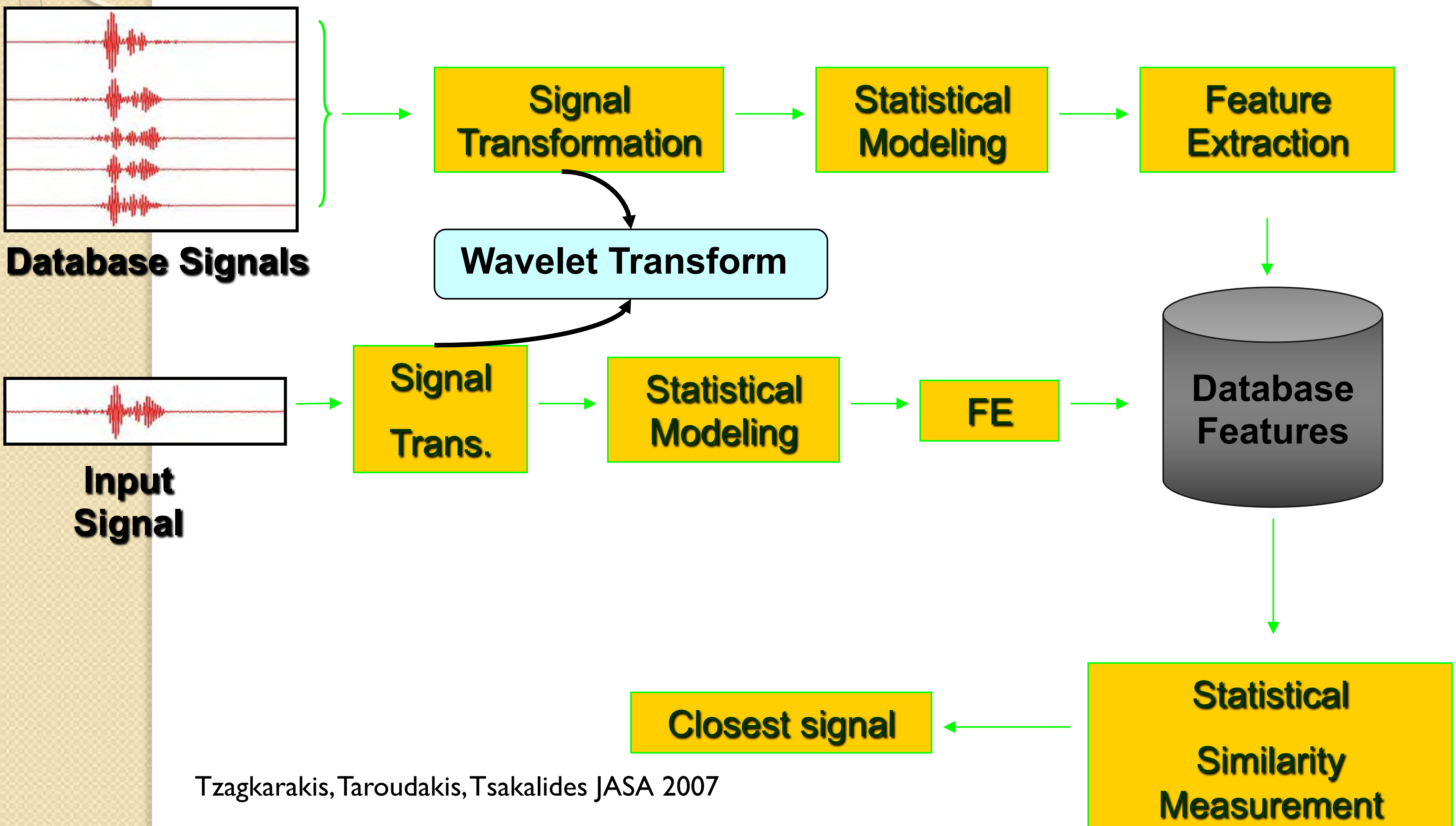
Characteristic Function

$$s[n] \leftrightarrow \boldsymbol{\theta} \equiv (\gamma_1, \alpha_1, \ldots.\gamma_4, a_4)$$

Signal Characterization

Taroudakis, Tzagkarakis, Tsakalides JASA 2006

# Inversion Procedure

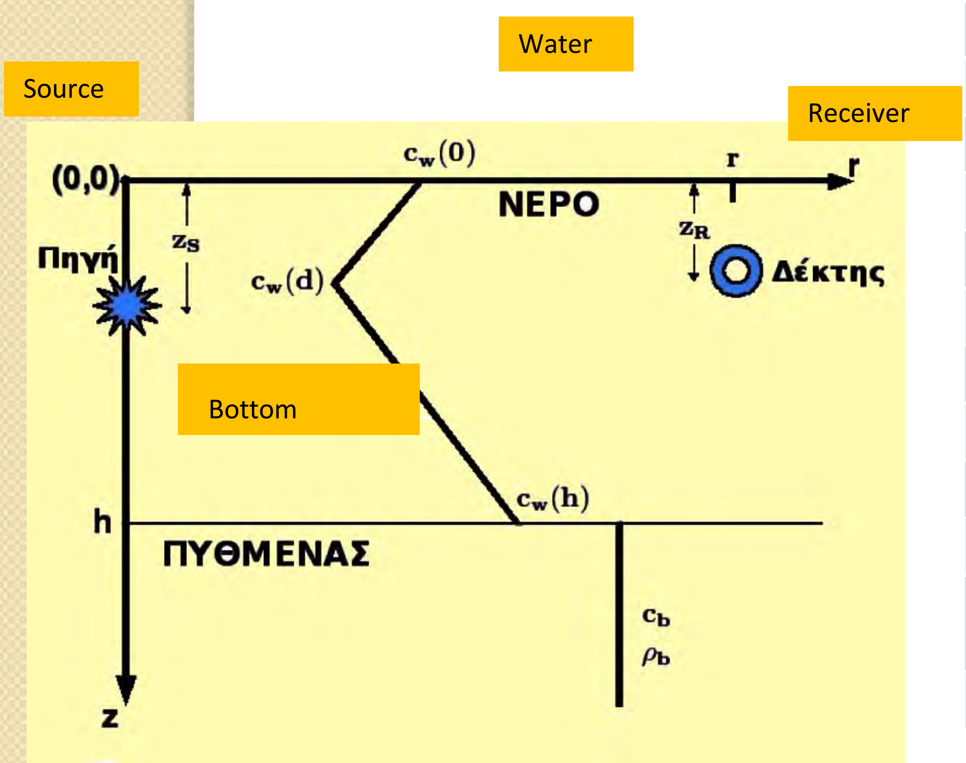



Tzagkarakis, Taroudakis, Tsakalides JASA 2007

# Inversion results using RBF NN

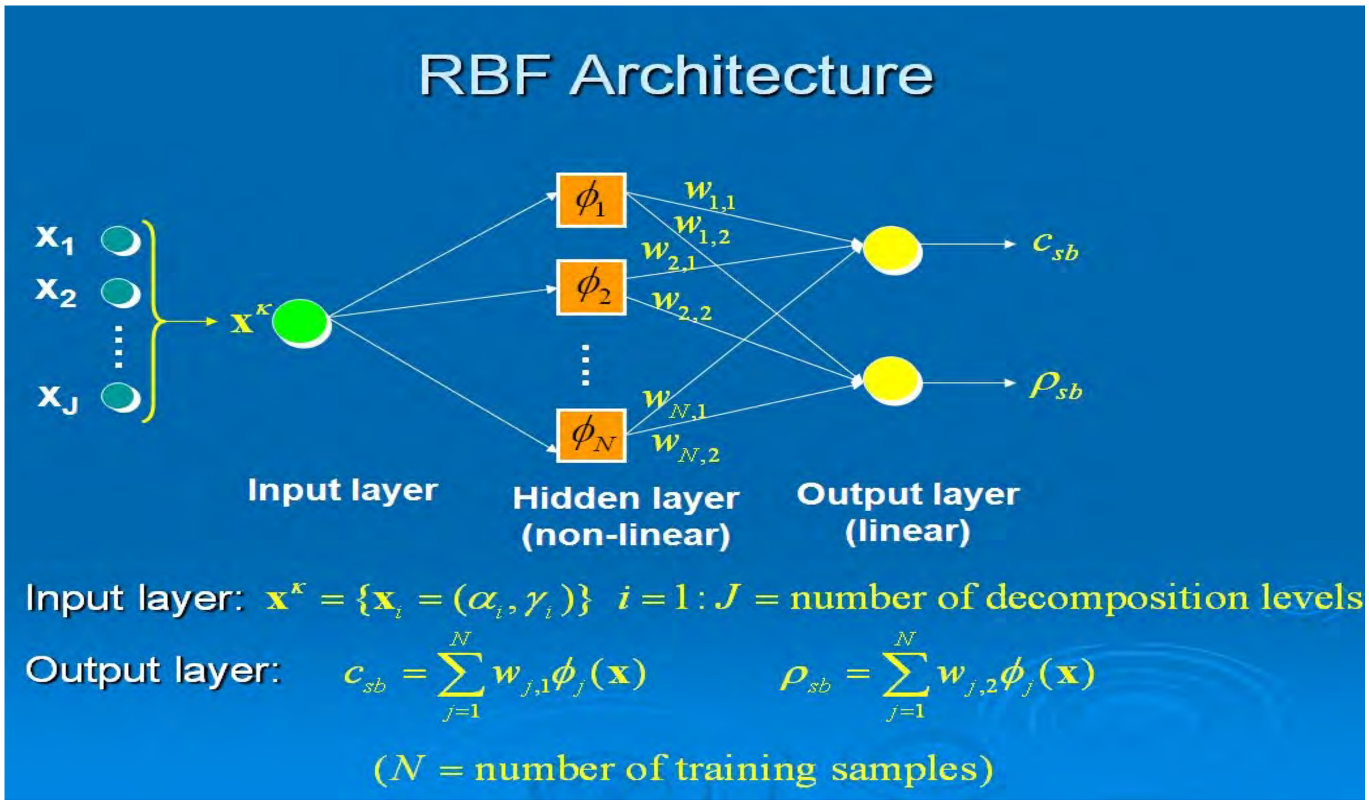
- A very simple simulated example
- Sea-bed classification with two parameters $c_b$ and $\rho_b$

$$\mathbf{m} = \left(c_b, \rho_b\right)$$




| Description | Symbol | True Value | Search Space |
|---|---|---|---|
| Water Depth | $h$ | 200 m | |
| Source Depth | $z_0$ | 100 m | |
| Receiver Depth | $z_R$ | 100 m | |
| Range | $R$ | 5000 m | |
| Central Frequency | $f0$ | 100 Hz | |
| Bandwidth | $\Delta f$ | 40 Hz | |
| Sound speed | $c_w(0)$ | 1500 m/sec | |
| | $c_w(d)$ | 1490 m/sec | |
| | $c_w(h)$ | 1515 m/sec | |
| Depth of the $c_{min}$ | $d$ | 50 m | |
| Sound speed in bottom | $c_b$ | 1600 m/sec | [1550,1650] |
| Bottom density | $\rho_b$ | 1200 kg/m3 | [1170,1240] |

# Inversion using RBF NN




Supervised training

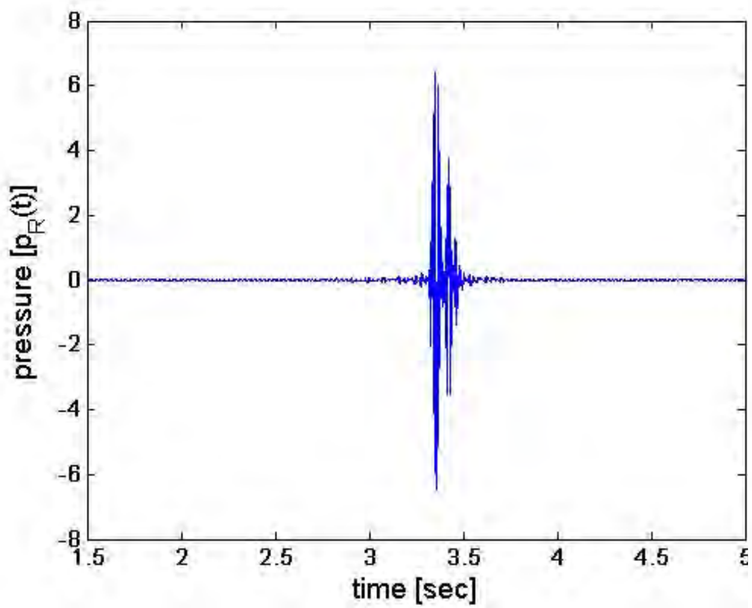
# Inversion results using RBF NN

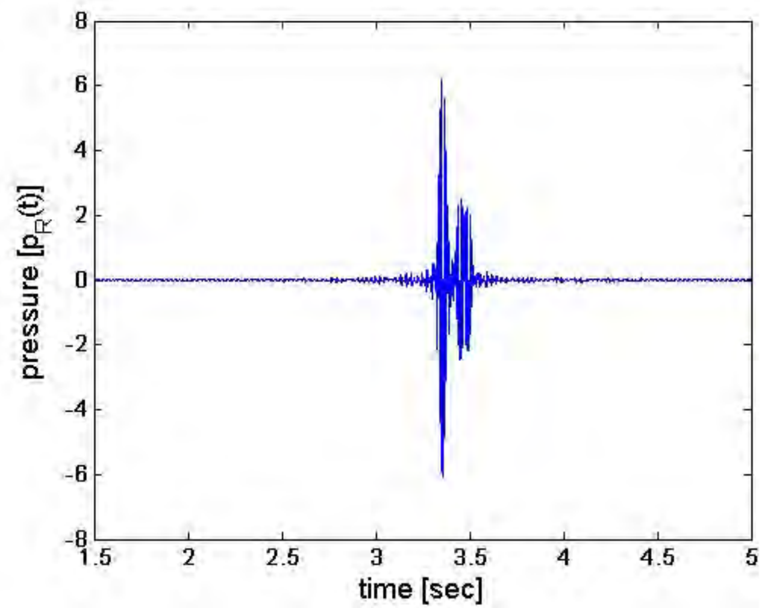
- Synthetic signals database from the search space (1550,1650)x( 1170,1240) using a forward propagation model (MODE1)
- Decompose each signal with a 3-level DWT (with db4 wavelet) and get the characteristic parameters using A-stable modelling (SaS)
- RBF NN training using the estimated *SαS* parameters of a subset of *M*=200 signals obtained from distinct environments within the pre-defined search space

For each environment input $\mathbf{x} = (\alpha_1, \gamma_1, ..., \alpha_4, \gamma_4)$

$$\mathbf{m} = (c_b, \rho_b) \qquad \mathbf{d} = (\alpha_1, \gamma_1, ..., \alpha_4, \gamma_4)_s$$

# Inversion results using RBF NN

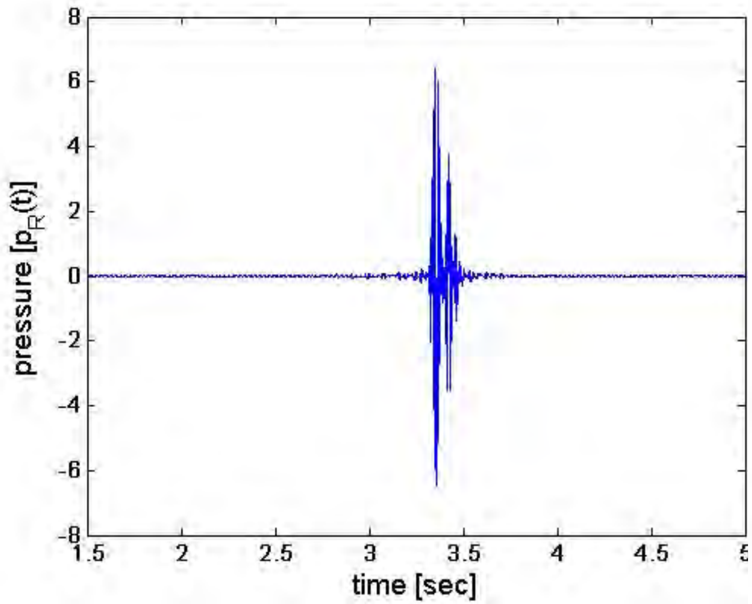


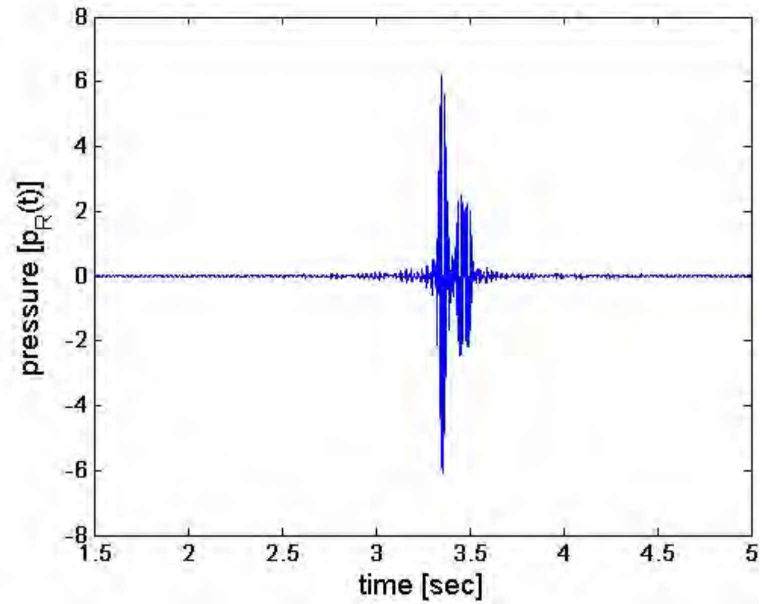




$$True:$$
$$(c_{sb}, \rho_{sb}) = (1570, 1185)$$

$$True:$$
$$(c_{sb}, \rho_{sb}) = (1600, 1200)$$

# Inversion results using RBF NN




$$True:$$
$$(c_{sb}, \rho_{sb}) = (1570, 1185)$$
$$Estimated:$$
$$(\hat{c}_{sb}, \hat{\rho}_{sb}) = (1569.4, 1181.8)$$

$$True:$$
$$(c_{sb}, \rho_{sb}) = (1600, 1200)$$
$$Estimated:$$
$$(\hat{c}_{sb}, \hat{\rho}_{sb}) = (1600.7, 1201.8)$$

# Additional notes

- Similarity measures using KLD

$$d_i = D(p(X;\boldsymbol{\theta}_{\mathbf{q}}) \| p(X;\boldsymbol{\theta}_{\mathbf{i}})) = \int p(x;\boldsymbol{\theta}_{\mathbf{q}}) \log \frac{p(x;\boldsymbol{\theta}_{\mathbf{q}})}{p(x;\boldsymbol{\theta}_{\mathbf{i}})} dx$$

- For optimum results the true signal should be denoised and deblurred
- A Genetic Algorithm may be applied instead of the NN.

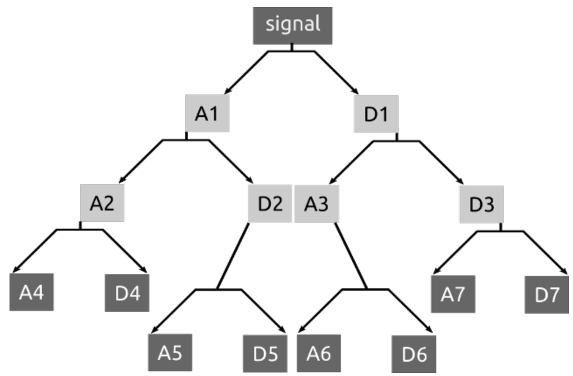
Taroudakis, Smaragdakis, Chapman JCA 2017
Taroudaki, Smaragdakis, Taroudakis, POMA 2016, 2018

# Hidden Markov Models

- Characterization of an underwater acoustic signal taking into account sequential features of a transformed version of it.

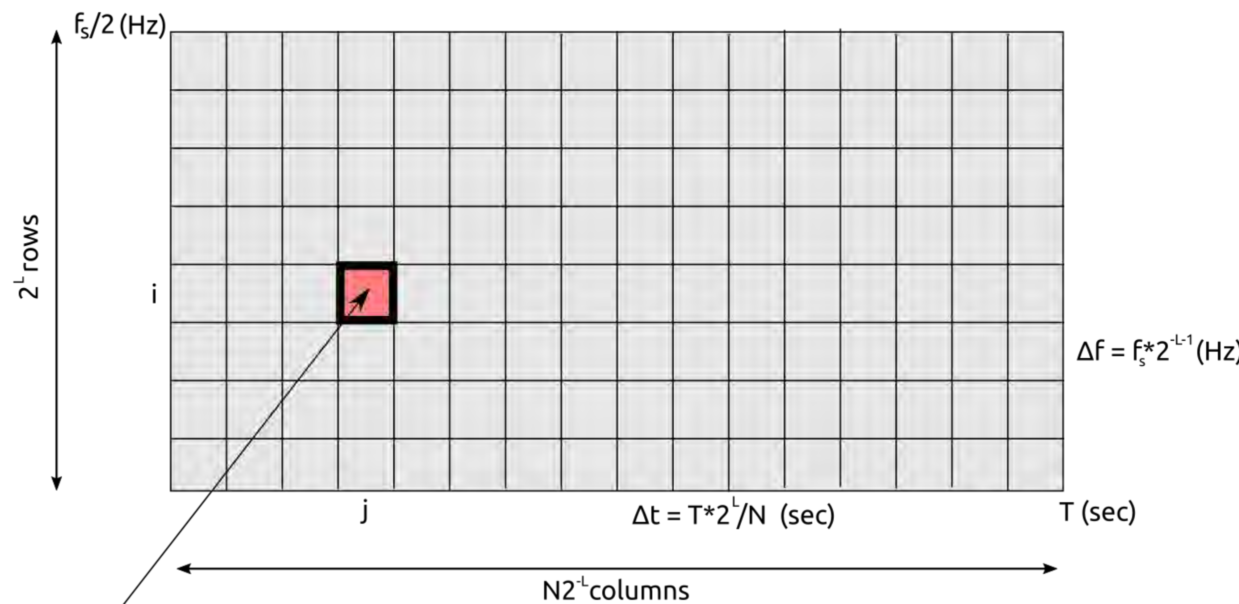
Smaragdakis, Taroudakis, JASA 2020

# Hidden Markov Models




3-Level Wavelet Packet Decomposition tree

Scalogram




Each element (i,j) of the matrix provides information for time [j-1,j]*Δt and frequency [i-1,i]*Δf windows.

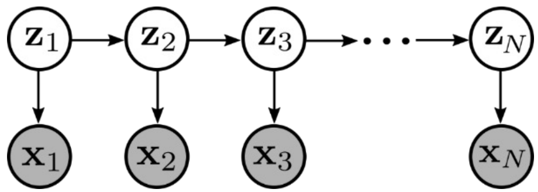
# Hidden Markov Models


Signal Scalogram Features -**X**

They are treated as stochastic variables and consist the sequence **X** of the direct observations.

The Markov process **Z** describes the fact that the elements of the stochastic sequence belong to specific **states** and that the elements of each time step may stay in the same state or belong to a different state.

# Hidden Markov Models



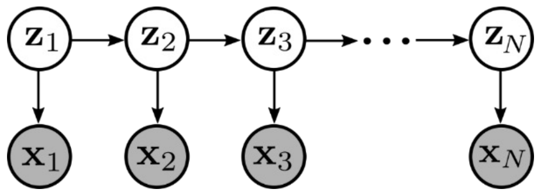

Latent Variables - **Z**

Signal Scalogram Features -**X**

The latent variables describe the association of the wavelet coefficients (Signal Scalogram Features) with the “states” establishing a probabilistic relationship between the given sequence representing the measured signal **X** and the Markov process **Z**

They are obtained by appropriate training using the transformed version of the signal.

# Hidden Markov Models




Latent Variables - **Y**

Signal Scalogram Features -**X**

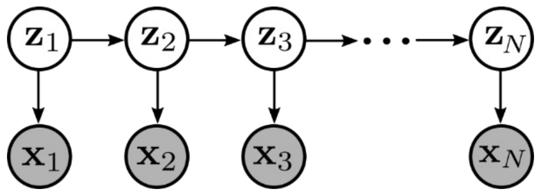
$$\boldsymbol{\lambda} = \{\boldsymbol{\pi}, \mathbf{A}, \boldsymbol{\theta}\}$$

**π** is the probability that the coefficients of the first time step are associated with each of the states.

**A** is a matrix indicating the probability that the wavelet coefficients of the time step *i* belonging to a specific state are associated with another state at the next time step.

**θ** are the emission probabilities that express the possibility that given a certain state, the wavelet coefficients at each time step belong to that state.

# Hidden Markov Models




Latent Variables

Signal Scalogram Features

$$\boldsymbol{\lambda} = \{\boldsymbol{\pi}, \mathbf{A}, \boldsymbol{\theta}\}$$

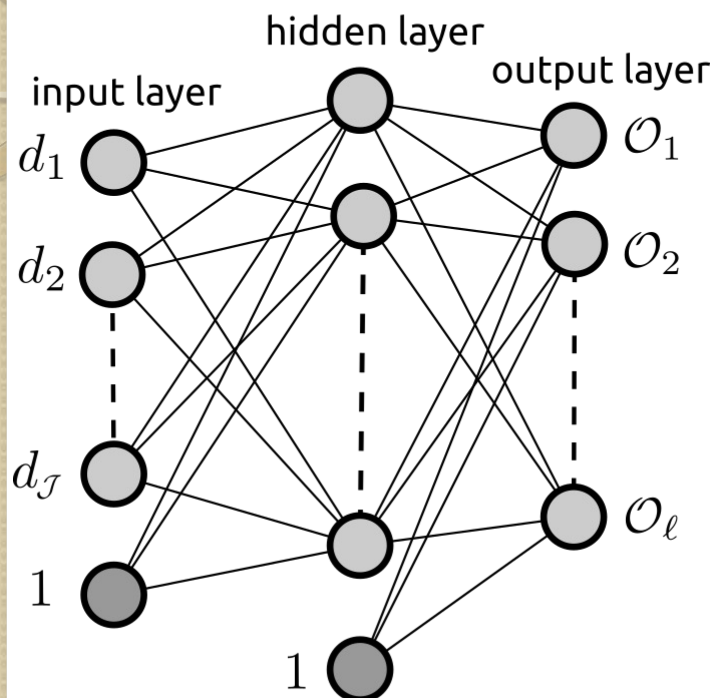
The signal is characterized with a single vector **d** (signal observable) with elements the Markov latent variables

$$\mathbf{X} \rightarrow (\mathbf{X}; \mathbf{Z}) \rightarrow \mathbf{d} \ \rightarrow \boldsymbol{\lambda}$$

$$s[n] \leftrightarrow \boldsymbol{\lambda} \equiv \{\boldsymbol{\pi}, \mathbf{A}, \boldsymbol{\theta}\} \qquad s[n] \leftrightarrow \boldsymbol{\theta} \equiv (\gamma_1, \alpha_1, \ldots.\gamma_4, a_4)$$

Statistical Characterization

# Using a Mixture Density Network




A MDN network is trained using a data set involving the parameters of the environment to be estimated and the corresponding Hidden Markov Variables

$$G = \{(\mathbf{m}^{(1)}, \mathbf{d}^{(1)}), \ldots, (\mathbf{m}^{(\mathrm{I})}, \mathbf{d}^{(\mathrm{I})})\}$$

The cost function

$$E(\mathbf{W}, \mathbf{b}) = -\sum_{i=1}^{\mathrm{I}} \ln \sum_{p=1}^{l} \pi_p(\mathbf{d}_i, \mathbf{W}, \mathbf{b}) \mathrm{N}\left(\mathbf{m}_i \mid \boldsymbol{\mu}_p(\mathbf{d}_i, \mathbf{W}, \mathbf{b}), \boldsymbol{\Sigma}_p(\mathbf{d}_i, \mathbf{W}, \mathbf{b})\right)$$

Output of the Network

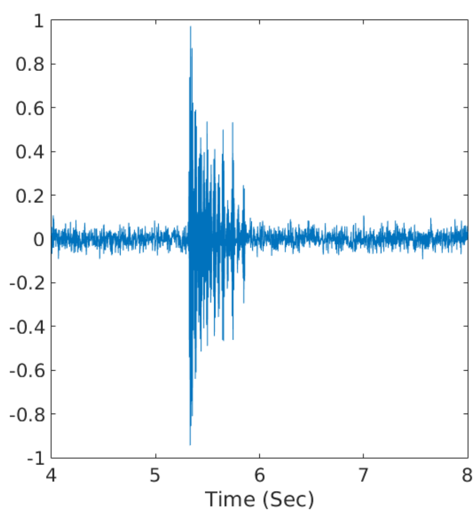
Posterior probability distribution

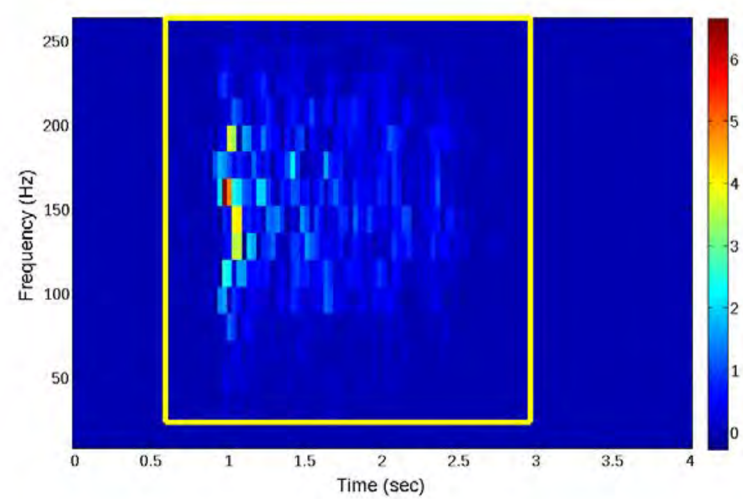
$$p(\mathbf{m} \mid \mathbf{d}) = \sum_{p=1}^{l} \pi_p(\mathbf{d}) \mathrm{N}\left(\mathbf{m} \mid \boldsymbol{\mu}_p(\mathbf{d}), \boldsymbol{\Sigma}_p(\mathbf{d})\right)$$

# Using a Mixture Density Network

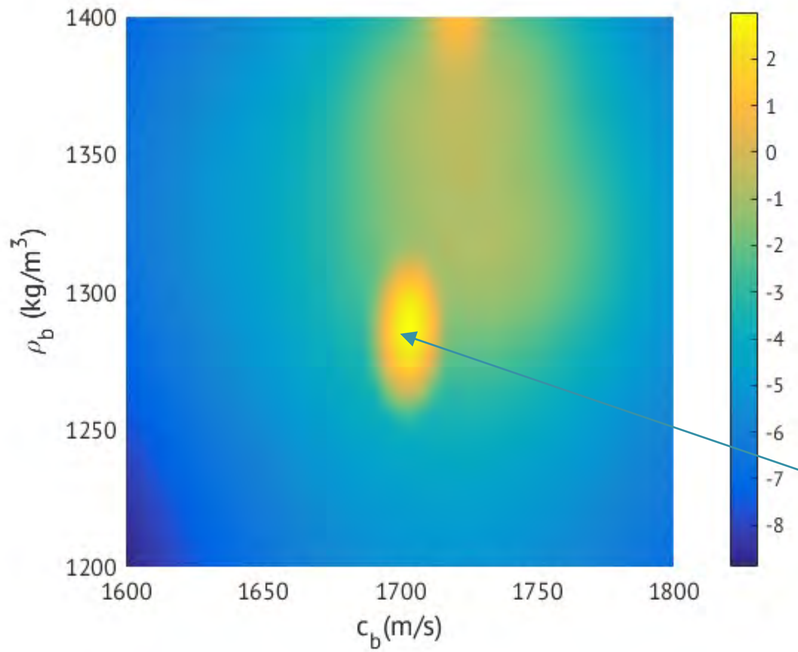
- Another very simple simulated example
- Sea-bed classification
- Pekeris environment

$$\mathbf{m}^{true} = (\rho_b^{true}, c_b^{true}) = (1300\ kg/m^3, 1700\ m/s)$$ To be estimated



# Using a Mixture Density Network




Log-scaled posterior joint density function

Global maximum

$$\mathbf{m}^{true} = (\rho_b^{true}, c_b^{true}) = (1300\,kg/m^3, 1700\,m/s)$$

# Using Genetic Algorithm

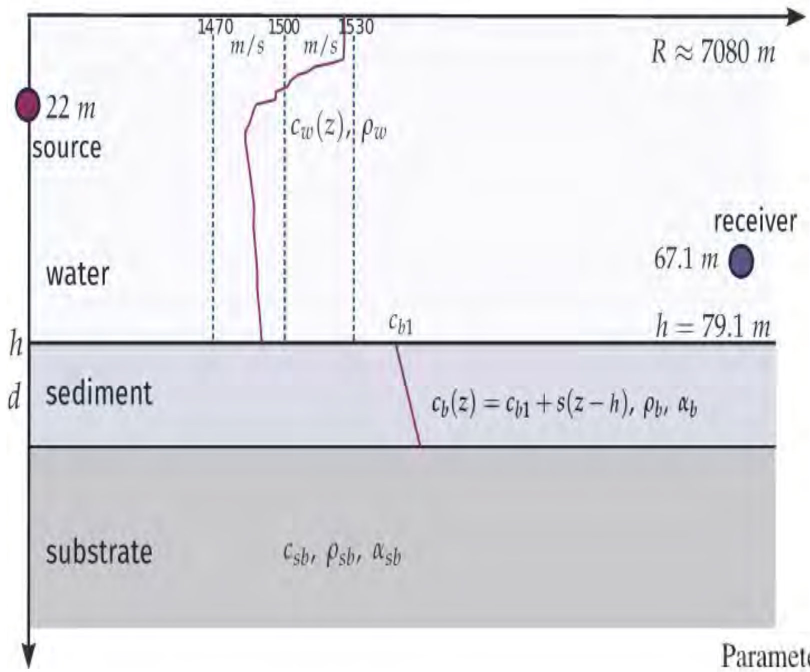
The similarity of two signal is measured comparing their associated HMMs through the Kullback-Leibler Divergence

$$\mathrm{D}\left(s_1\left[n\right],s_2\left[n\right]\right)=\mathrm{D}\left(\boldsymbol{\lambda}_1,\boldsymbol{\lambda}_2\right)$$

Use GA as the optimization process and seek the model parameters that generate a replica signal with the best resemblance to a recorded one on the basis of the similarities of their associated HMMs.

Using GA, we obtain a generation of possible solutions

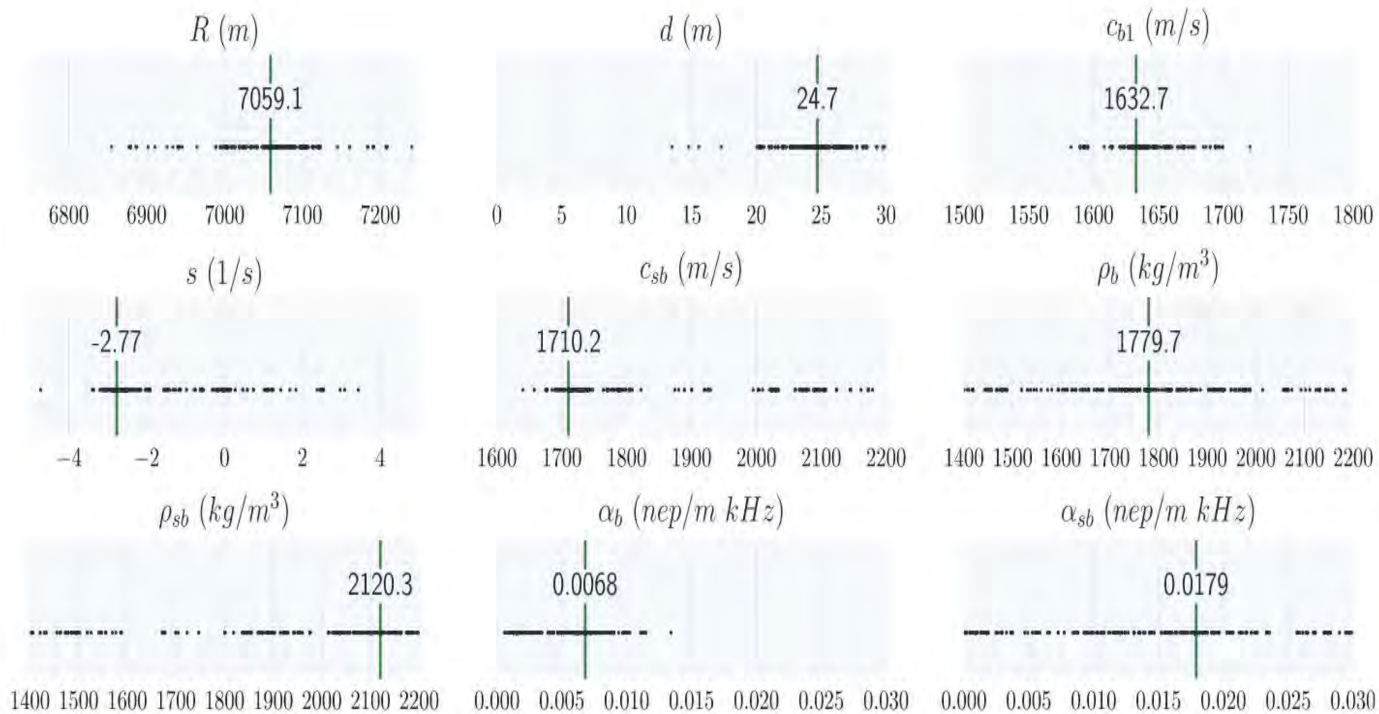
# Using Genetic Algorithm

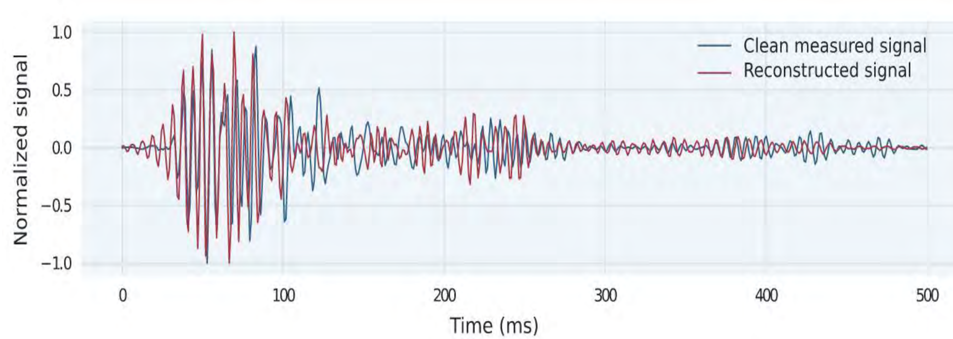



The SW06 experiment

| Parameters | Units | Search space |
|---|---|---|
| Range | $R$ (m) | [6750, 7250] |
| Sediment thickness | $d$ (m) | [0, 30] |
| Top Sediment sound speed | $c_{b1}$ (m/s) | [1500, 1800] |
| Sediment sound speed slope | $s$ (1/s) | [−5, 5] |
| Substrate sound speed | $c_{sb}$ (m/s) | [1600, 2200] |
| Sediment density | $\rho_b$ (kg/m$^3$) | [1400, 2200] |
| Substrate density | $\rho_{sb}$ (kg/m$^3$) | [1400, 2200] |
| Sediment attenuation | $\alpha_b$ (nep/mkHz) | [0,0.03] |
| Substrate attenuation | $\alpha_{sb}$ (nep/mkHz) | [0,0.03] |

# Using Genetic Algorithm



# Conclusions – Future Trends

Machine Learning can be proven a very efficient companion of the methods applied in acoustical oceanography for ocean acoustic tomography, sea-bed classification.

This type of techniques are now implemented in problems of monitoring the seismicity in Greek areas by exploiting their ability to analyze big data on earthquake occurrence and predict future trends on seismic events and associated parameters.

# Collaborators

- Panayiotis Tsakalides
- George Tzagkarakis
- John Mastrokalos
- Ross Chapman
- Stan Dosso
- Victoria Taroudaki

Ευχαριστώ για την προσοχή σας

Τις καλύτερες ευχές μου στο Μάκη
για υγεία, μακροημέρευση και ακόμη περισσότερη συνεισφορά στην επιστήμη και την εκπαίδευση.