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An Overview: The Application of Machine-Learning method in Underwater Acoustic

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Outline

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- Underwater Acoustic Environment
- Definition of Machine Learning Problem

Data and Method

- Database: Simulation or Real
- Machine Learning VS. Deep Learning
- Preprocessing and Feature Extract
- The application in Underwater Acoustic

My PhD. Plan

Problem Definition: Underwater Acoustic Environment

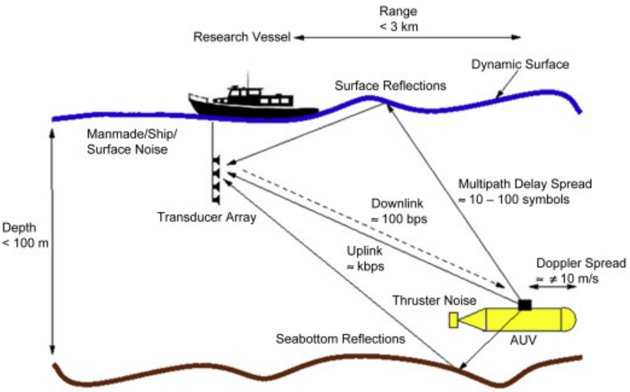

Figure: Underwater Acoustic Environment [1]

- The source-receiver condition
- Seabed geoacoustic parameters
- The acoustic propagation model

Definition of Machine Learning Problem

Dataset Structure

The general dataset structure (so-called sample pairs) is

$$\{\boldsymbol{x}_i, y_i\}_{i=1}^{N} \quad (1)$$

in which N is the amount of samples, $\boldsymbol{x}_i$ is the feature of the *ith* sample pair, y_i is the *ith* corresponding label.

Supervised Learning

A machine learning task of learning a function that maps an input to an output based on example input-output pairs.[2]

1. Classification: $f(\boldsymbol{x}) \rightarrow y$(discrete categories)
2. Regression: $f(\boldsymbol{x}) \rightarrow y$(real number)
   where $f(.)$ is the latent rule learned by machine learning method.

Widely applied in underwater acoustic field: **localization, geoacoustic inversion, ...**

Database: Simulation or Real

Most of scientists use the propagation models to create training dataset:

- ORCA[3, 4]
- KRAKEN[5, 6, 7, 8, 9, 10, 11]
- SOLID [12]
- SAFARI-code [13]
- Parabolic Equation [14]

Few use the ocean experiment data to created training dataset:

- TRIAL SABLE Experiment [3]
- RAFAL Water-Tank Experiment [14]
- Santa Barbara Channel Experiment [10]
- Noise09 Experiment [9]

Method: Machine Learning VS. Deep Learning

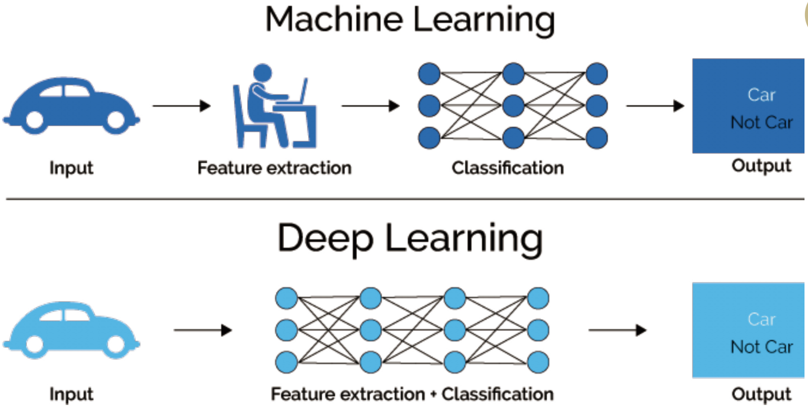

Figure: Machine Learning VS. Deep Learning

Preprocessing and Feature Extract

For Geoacoustic Inversion

- **Raw Acoustic field** [13, 3]
- Angles of incidence [15]
- Amplitude of Green's function [13]
- Transmission Losses [16]
- Relative Amplitudes of distinct peaks of signal[11]
- Signal Kurtosis [11]
- Signal Strength [11]
- Peak Level [4]
- Integrated Intensity[4]

For Geoacoustic Inversion

- **Raw Acoustic field**[6]
- Phase Difference [17]
- Amplitude of acoustic pressure after FFT[14]
- Normalized sample covariance matirx [10, 9]
- Eigenvector of raw acoustic field [6]
- Segment Normalized [7, 8]

Method: The application in Underwater Acoustic

1. Classic Machine Learning:
   - Shallow Artificial Neural Network:
     - Multilayer Perceptron [12, 17, 15, 16, 3, 10, 9, 5, 4]
     - Radial Basis Function (RBF) network[13]
     - Generalized Regression Neural Network (GRNN) [5]
   - Linear regression[14]
   - Kernel regression [14]
   - Support Vector Machine (SVM) [10]
   - Random Forests (RF) [9]
   - Generalized additive model [11]
2. Deep Neural Network (**Deep Learning**)
   - Time delay neural network (TDNN) [6]
   - Convolutional Neural Network (CNN) [6, 7]
   - Residual Neural Networks [8]

Research Interest: Geoacoustic Inversion based on Deep Learning

Reason

- Significant importance for underwater acoustic modeling
- Hard to create an appropriate ML dataset (**Real data**)
- Fewer studies based on deep learning

Step1: Database Construction

Simulation Database

- different acoustic propagation models
- different geoacoustic parameters (grids, intervals)

Real Database

- Public experiments with labeled data (the SWellEx96 Experiment,...)
- **Label supplement method** for those unlabeled data

Alternative way : Marine Science

- Argo:
  The broad-scale global array of temperature & salinity profiling floats
- Simple Ocean Data Assimilation (SODA):
  providing 3D Velocity, SST, Salinity, potential temperature, sea surface height,...

Step2: Method Design

Option 1. Supervised Learning: Design a special network

- Convolutional Neural Network (CNN)
- Long Short-Term Memory (LSTM)
- ...

Option 2. Unsupervised Learning: Label Supplement & Feature Extraction and Analysis

- Auto-encoder (AE)
- K-means
- ...

Step3: Evaluation

Compare with conventional underwater acoustic methods

- Match Field Processing (MFP)
- Genetic Algorithm (GA)
- ...

Validation based on real dataset

- labeled dataset
- re-labeled dataset

References I

[1] .“Chapter 14 - Underwater Acoustic Measurements and Their Applications”. In: *Applied Underwater Acoustics*. Ed. by Thomas H. Neighbors and David Bradley. Elsevier, 2017, pp. 889–947. ISBN: 978-0-12-811240-3. DOI: https://doi.org/10.1016/B978-0-12-811240-3.00014-X.

[2] Stuart J Russell and Peter Norvig. *Artificial intelligence: a modern approach*. Malaysia; Pearson Education Limited, 2016.

[3] Jeremy Benson, N Ross Chapman, and Andreas Antoniou. “Geoacoustic model inversion using artificial neural networks”. In: *Inverse Problems* 16.6 (2000), p. 1627.

[4] David F Van Komen et al. “A feedforward neural network for source range and ocean seabed classification using time-domain features”. In: *Proceedings of Meetings on Acoustics 177ASA*. Vol. 36. 1. Acoustical Society of America. 2019, p. 070003.

[5] Yun Wang and Hua Peng. “Underwater acoustic source localization using generalized regression neural network”. In: *The Journal of the Acoustical Society of America* 143.4 (2018), pp. 2321–2331.

[6] Zhaoqiong Huang et al. “Source localization using deep neural networks in a shallow water environment”. In: *The Journal of the Acoustical Society of America* 143.5 (2018), pp. 2922–2932.

References II

[7] Yi-Ning Liu, Hai-Qiang Niu, and Zheng-Lin Li. "Source Ranging Using Ensemble Convolutional Networks in the Direct Zone of Deep Water". In: *Chinese Physics Letters* 36.4 (2019), p. 044302.

[8] Haiqiang Niu et al. "Deep-learning source localization using multi-frequency magnitude-only data". In: *The Journal of the Acoustical Society of America* 146.1 (2019), pp. 211–222.

[9] Haiqiang Niu, Emma Reeves, and Peter Gerstoft. "Source localization in an ocean waveguide using supervised machine learning". In: *The Journal of the Acoustical Society of America* 142.3 (2017), pp. 1176–1188.

[10] Haiqiang Niu, Emma Ozanich, and Peter Gerstoft. "Ship localization in Santa Barbara Channel using machine learning classifiers". In: *The Journal of the Acoustical Society of America* 142.5 (2017), EL455–EL460.

[11] Jacob Piccolo, George Haramuniz, and Zoi-Heleni Michalopoulou. "Geoacoustic inversion with generalized additive models". In: *The Journal of the Acoustical Society of America* 145.6 (2019), EL463–EL468.

[12] John M Ozard, Pierre Zakarauskas, and Peter Ko. "An artificial neural network for range and depth discrimination in matched field processing". In: *The Journal of the Acoustical Society of America* 90.5 (1991), pp. 2658–2663.

References III

[13] Andrea Caiti and Sergio M Jesus. "Acoustic estimation of seafloor parameters: A radial basis functions approach". In: *The Journal of the Acoustical Society of America* 100.3 (1996), pp. 1473–1481.

[14] Riwal Lefort, Gaultier Real, and Angélique Drémeau. "Direct regressions for underwater acoustic source localization in fluctuating oceans". In: *Applied Acoustics* 116 (2017), pp. 303–310.

[15] Z-H Michalopoulou, Dimitri Alexandrou, and Christian de Moustier. "Application of neural and statistical classifiers to the problem of seafloor characterization". In: *IEEE Journal of Oceanic Engineering* 20.3 (1995), pp. 190–197.

[16] Yann Stephan, Xavier Demoulin, and Olivier Sarzeaud. "Neural direct approaches for geoacoustic inversion". In: *Journal of Computational Acoustics* 6.01n02 (1998), pp. 151–166.

[17] Ben Zion Steinberg et al. "A neural network approach to source localization". In: *The Journal of the Acoustical Society of America* 90.4 (1991), pp. 2081–2090.

Thank you!