Enhancing model based acoustic localisation using quantum annealing

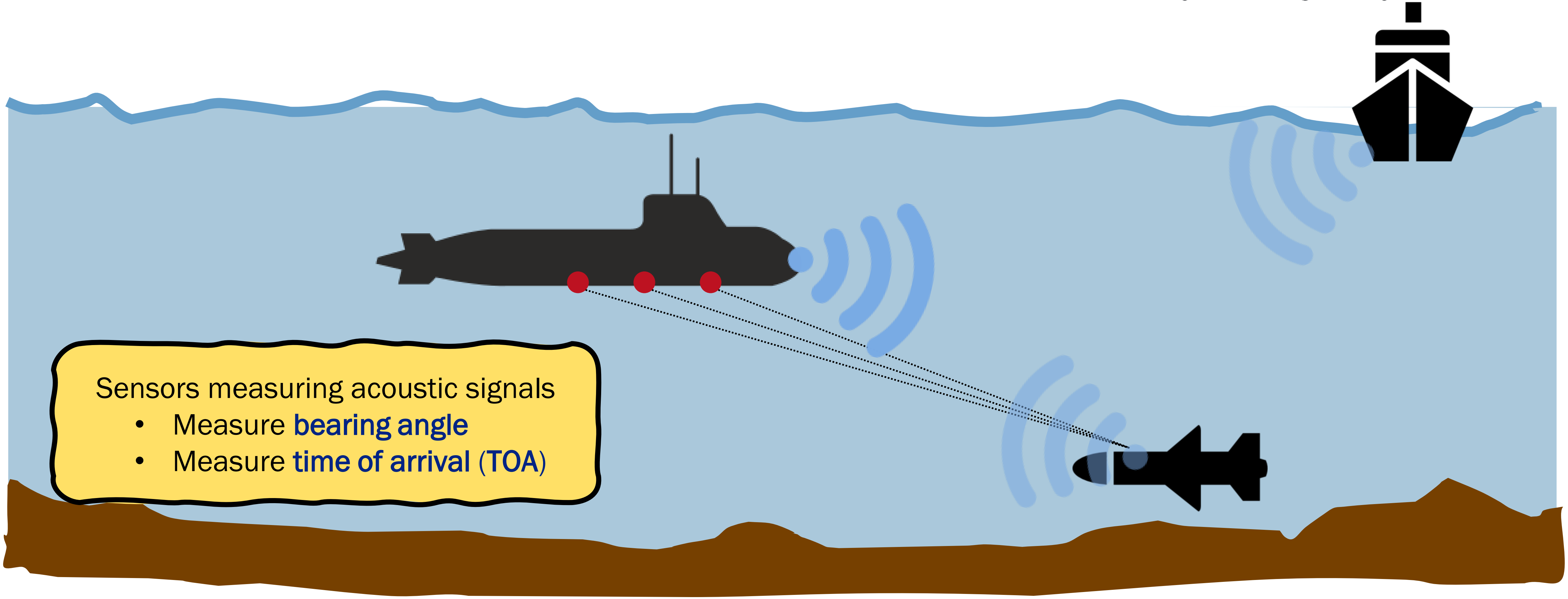
R.S. Wezeman MSc | Tariq Bontekoe MSc |
Dr. Sander von Benda-Beckmann|
Prof. dr. Frank Phillipson

TNO innovation for life

Underwater target localisation

Acoustic localisation is the use of sound to **determine the distance and direction** of its source or reflector.

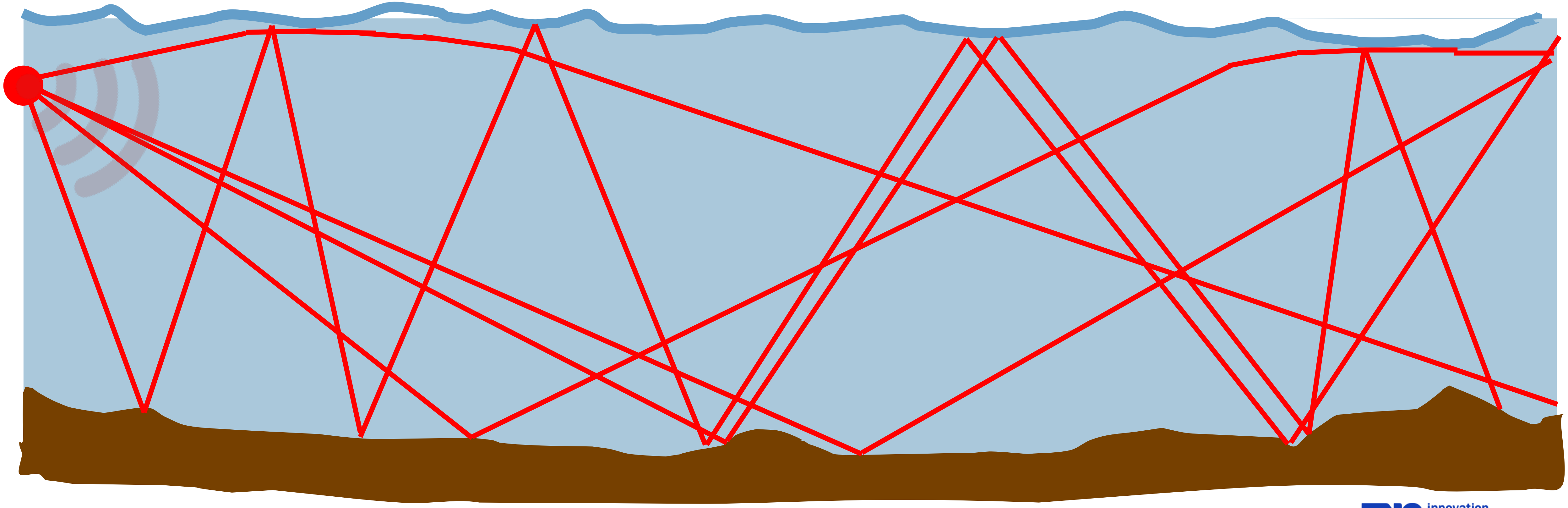
- **Passive acoustic localisation:** Involves detection of sound/vibration created by the target object.



Acoustic underwater propagation

Assumption of linear propagation of acoustic waves is not true underwater.

- ***Reflections*** through the ocean's bottom or ocean's surface result in loss of intensity
- ***Variable sound speed.*** The speed of acoustic waves depends on many parameters such as: *temperature, pressure (depth) and salinity*



Model-based acoustic localisation

*A typical way to solve an acoustic localisation problem is by using a **model-based approach**.*

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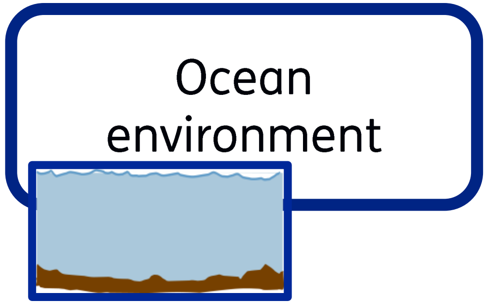

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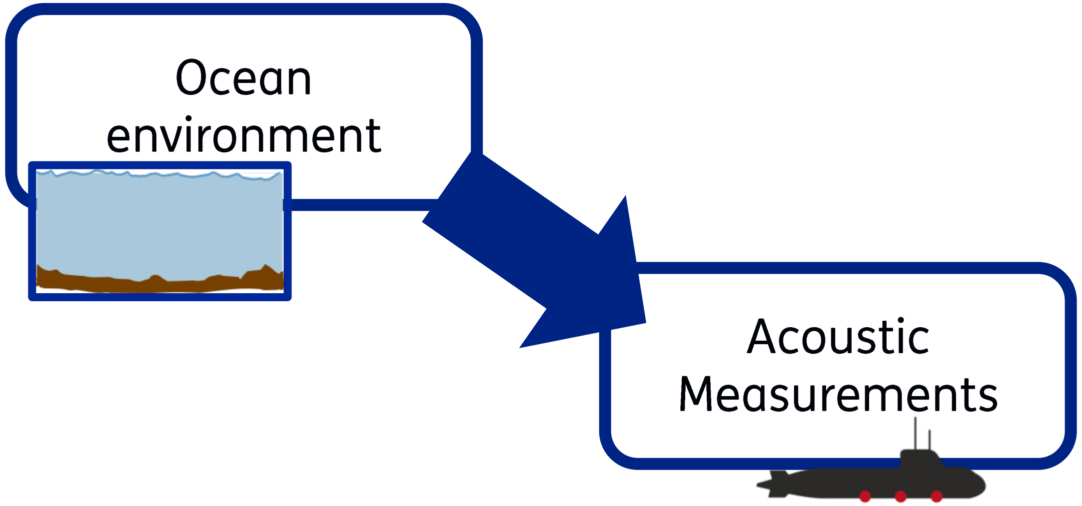

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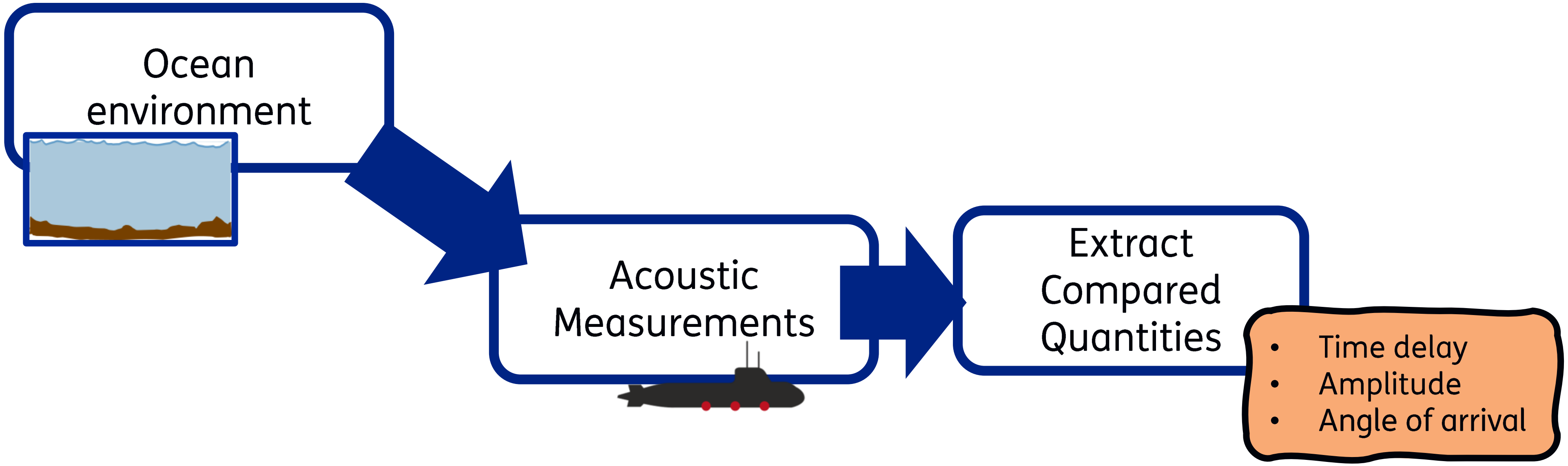

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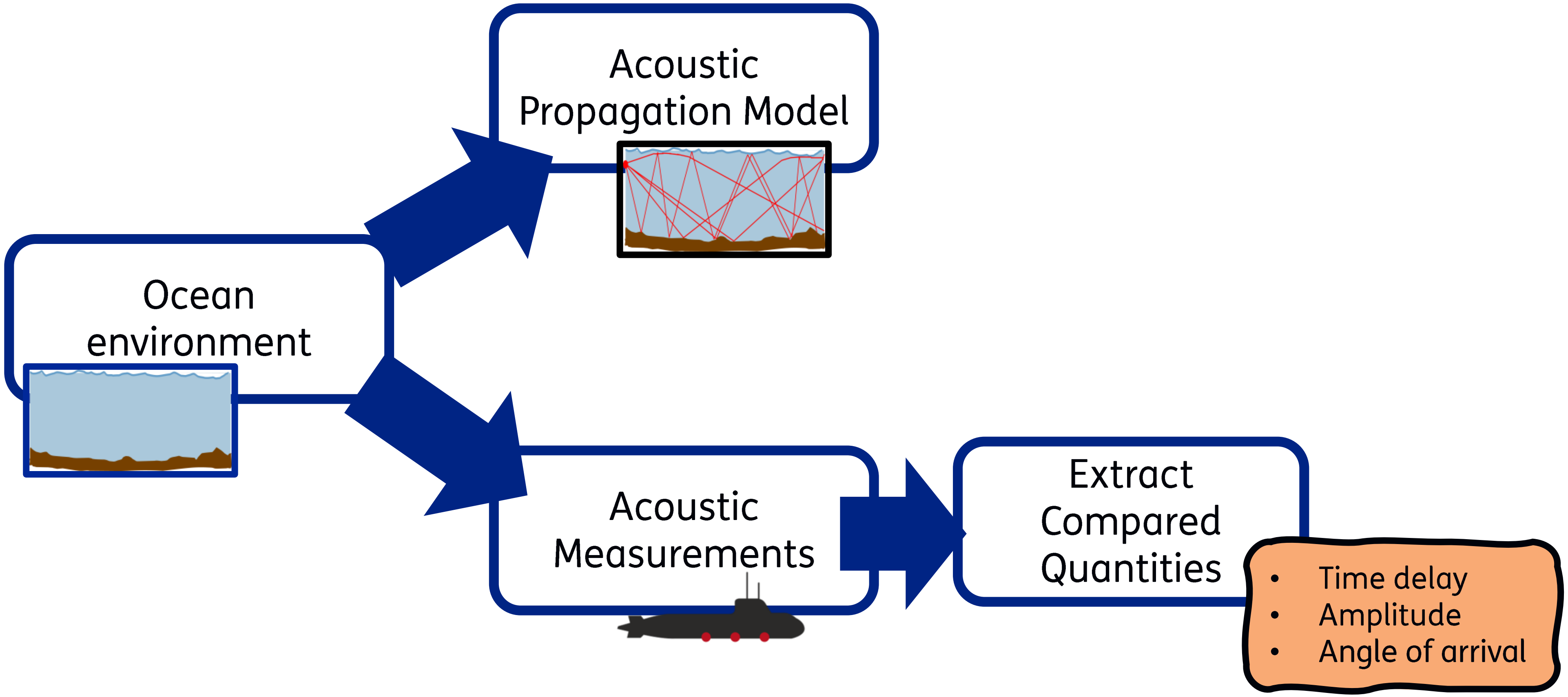

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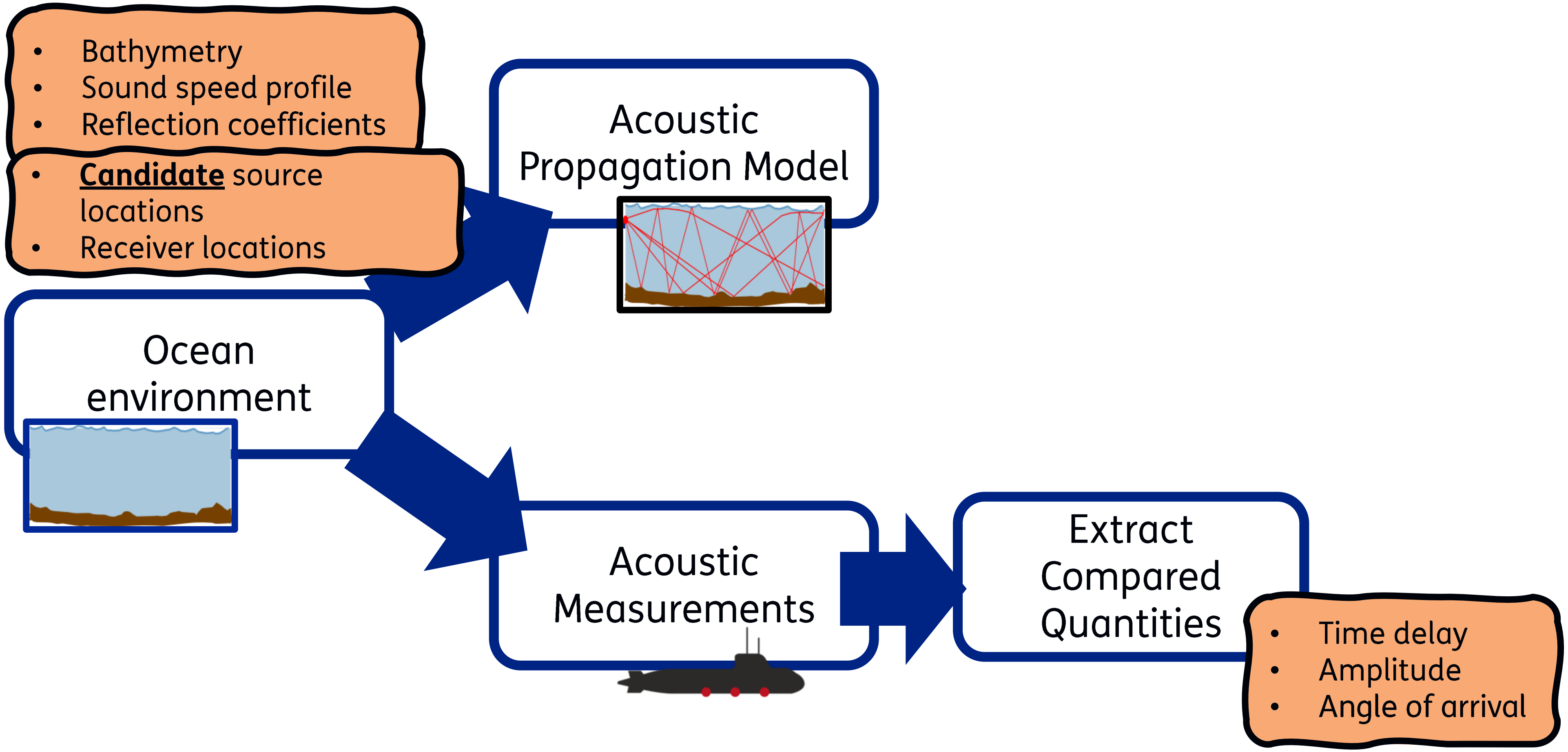

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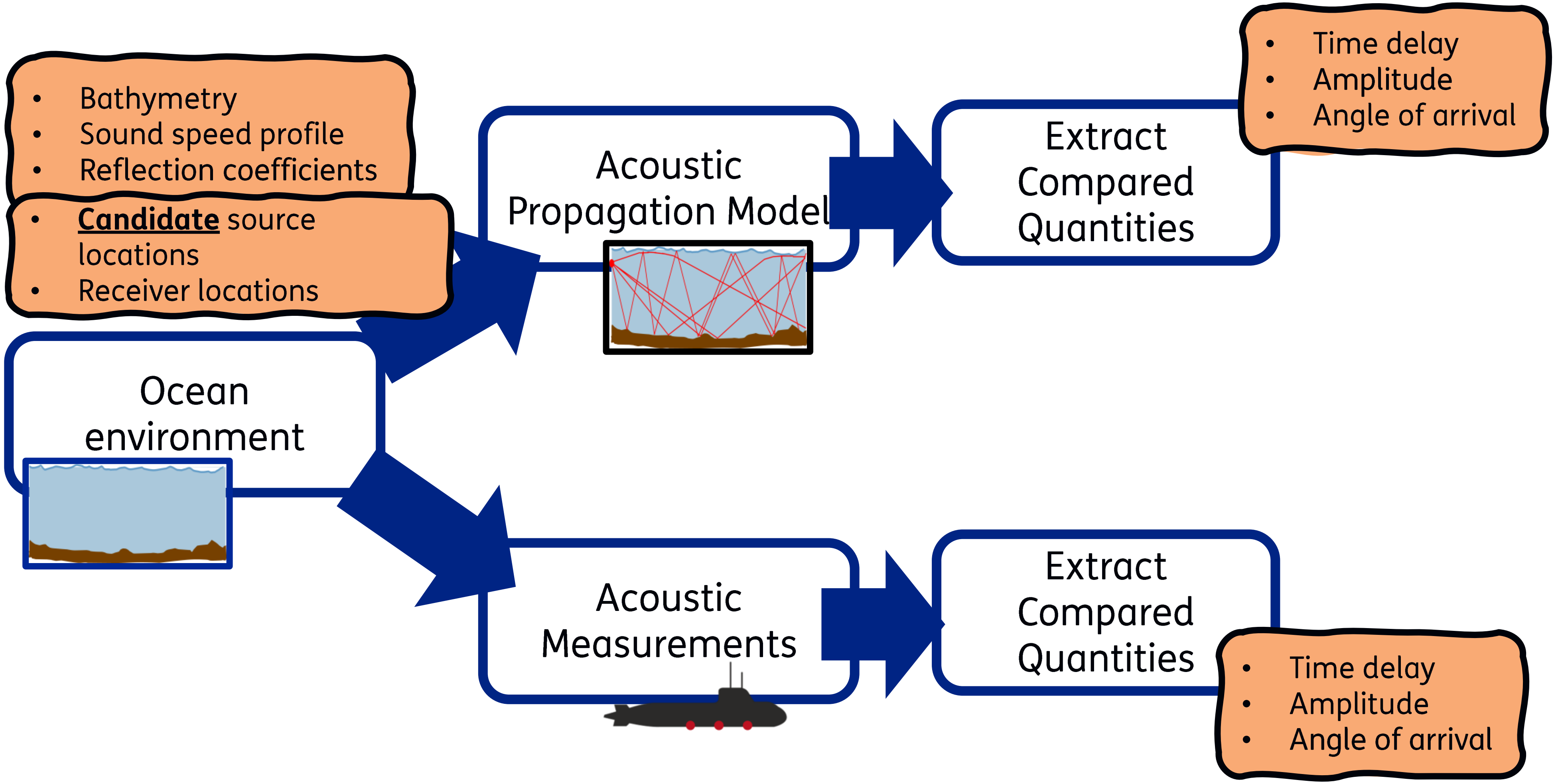

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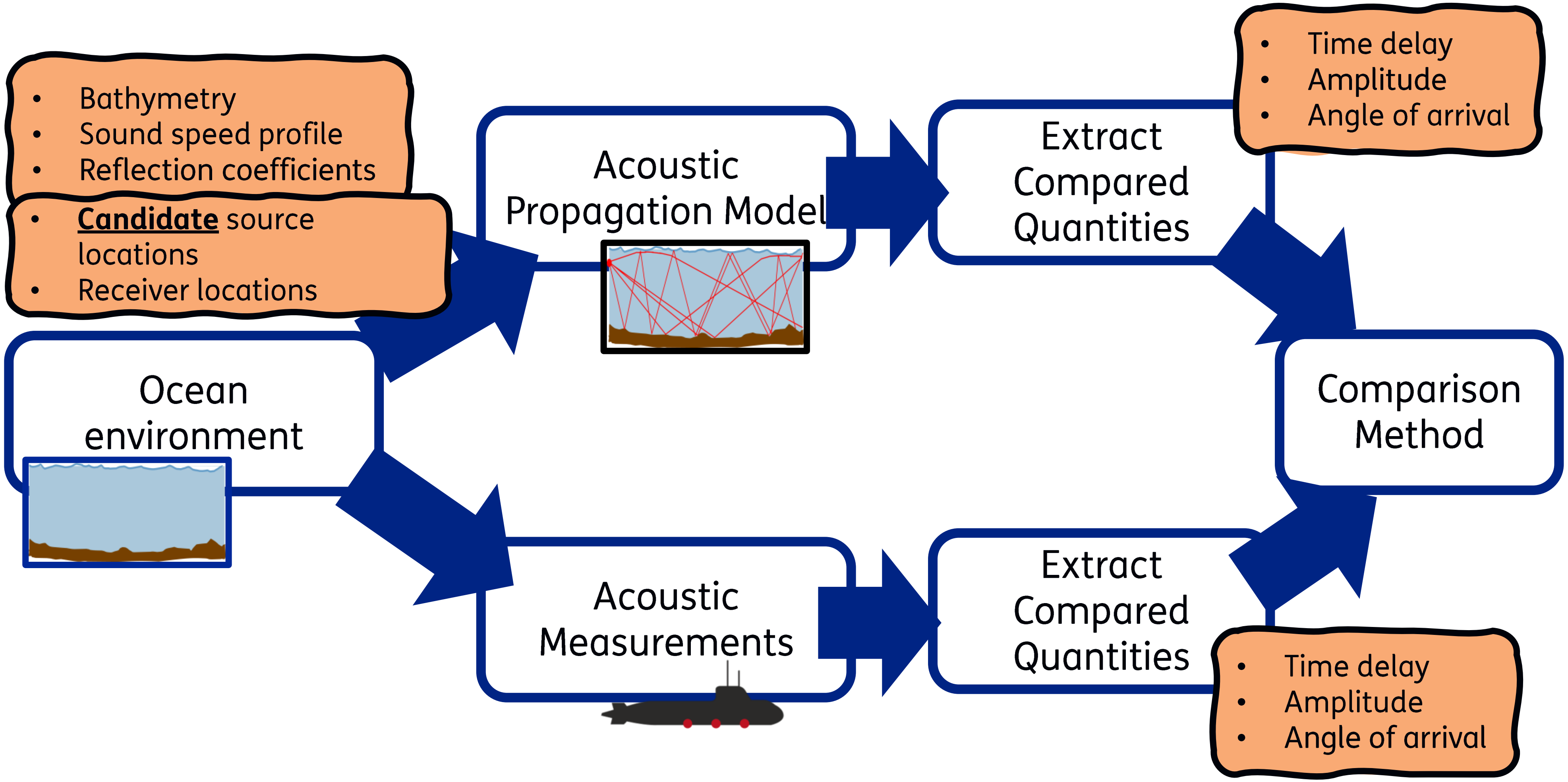

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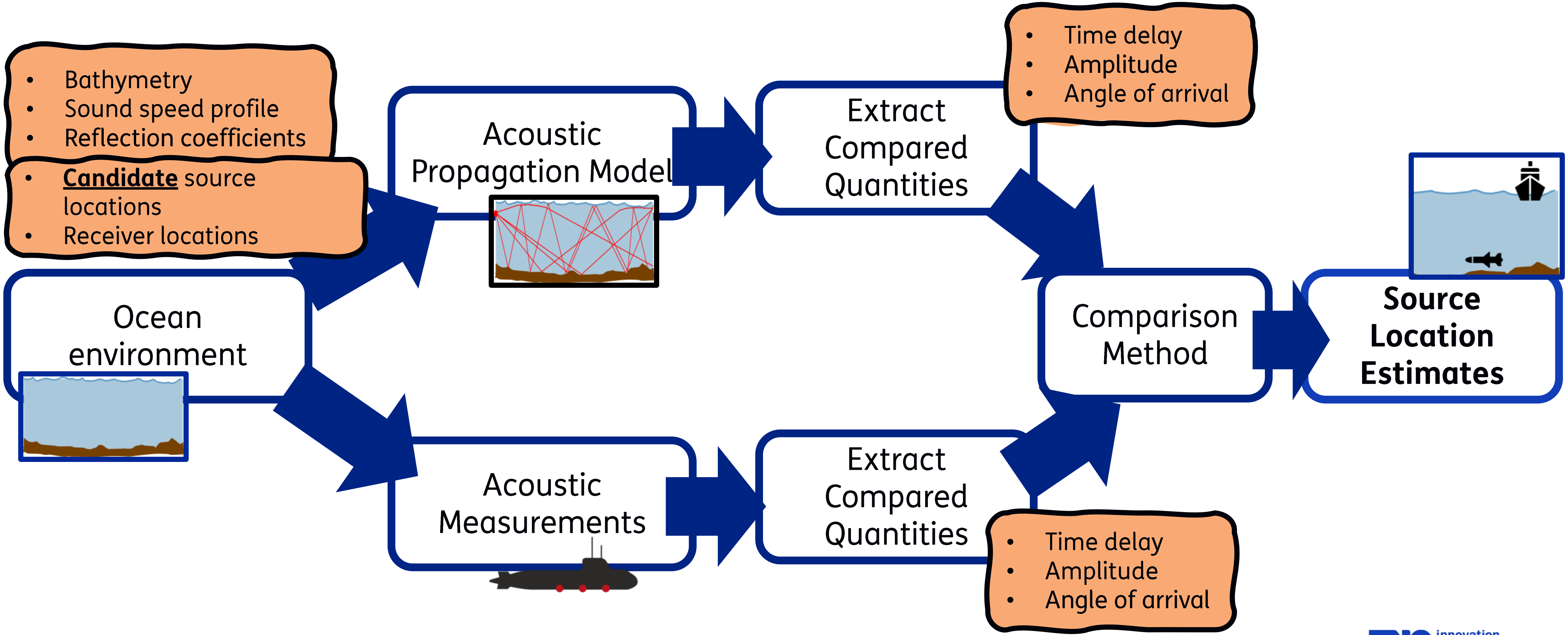


Model-based acoustic localisation

A typical

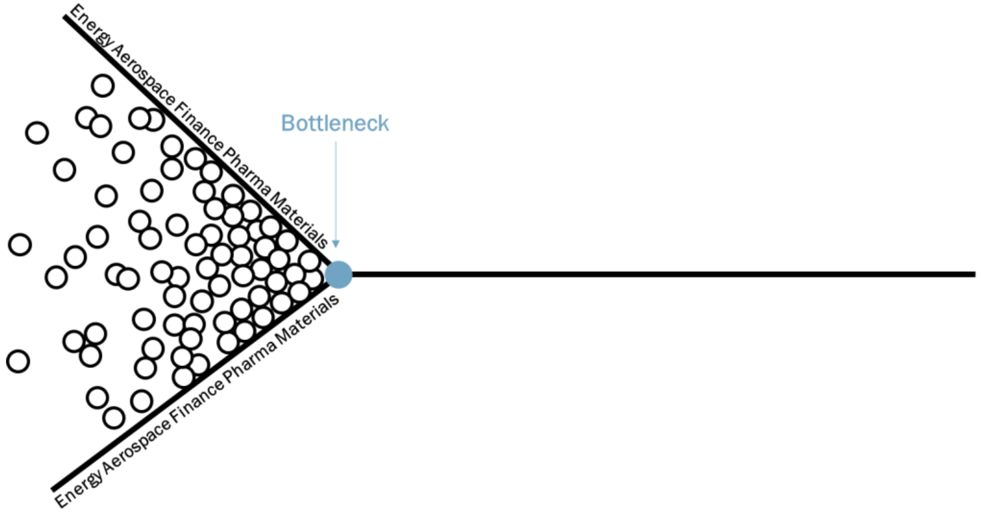
- Bathyme
- Sound sp
- Reflectio coefficie

- **Candidate** locations
- Receiver loca

Ocean environment

Ideally these calculations are performed on **real-time** data on board on a submarine

Applications are limited by the available computational power.



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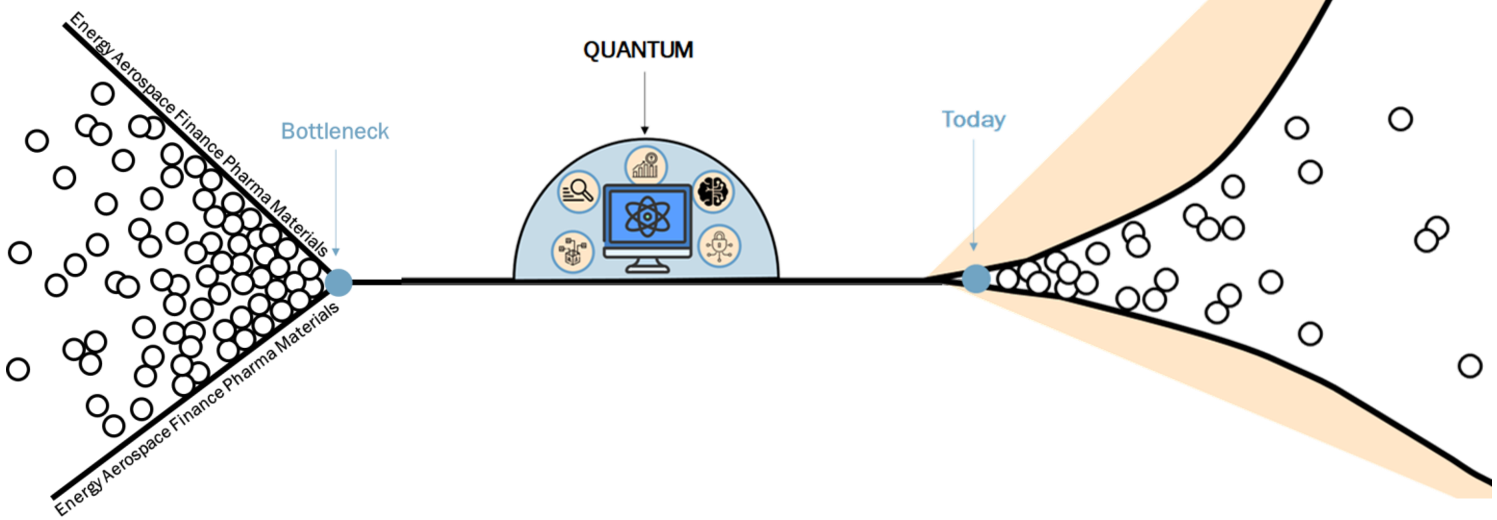

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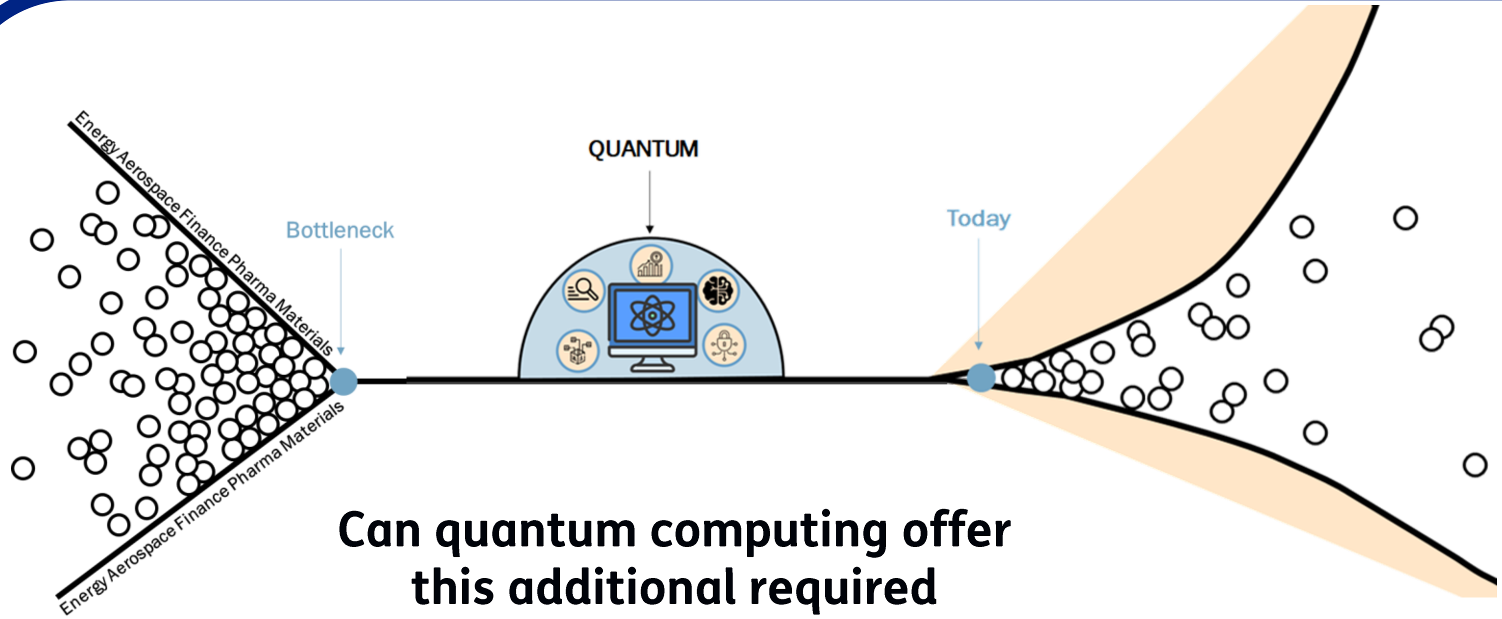
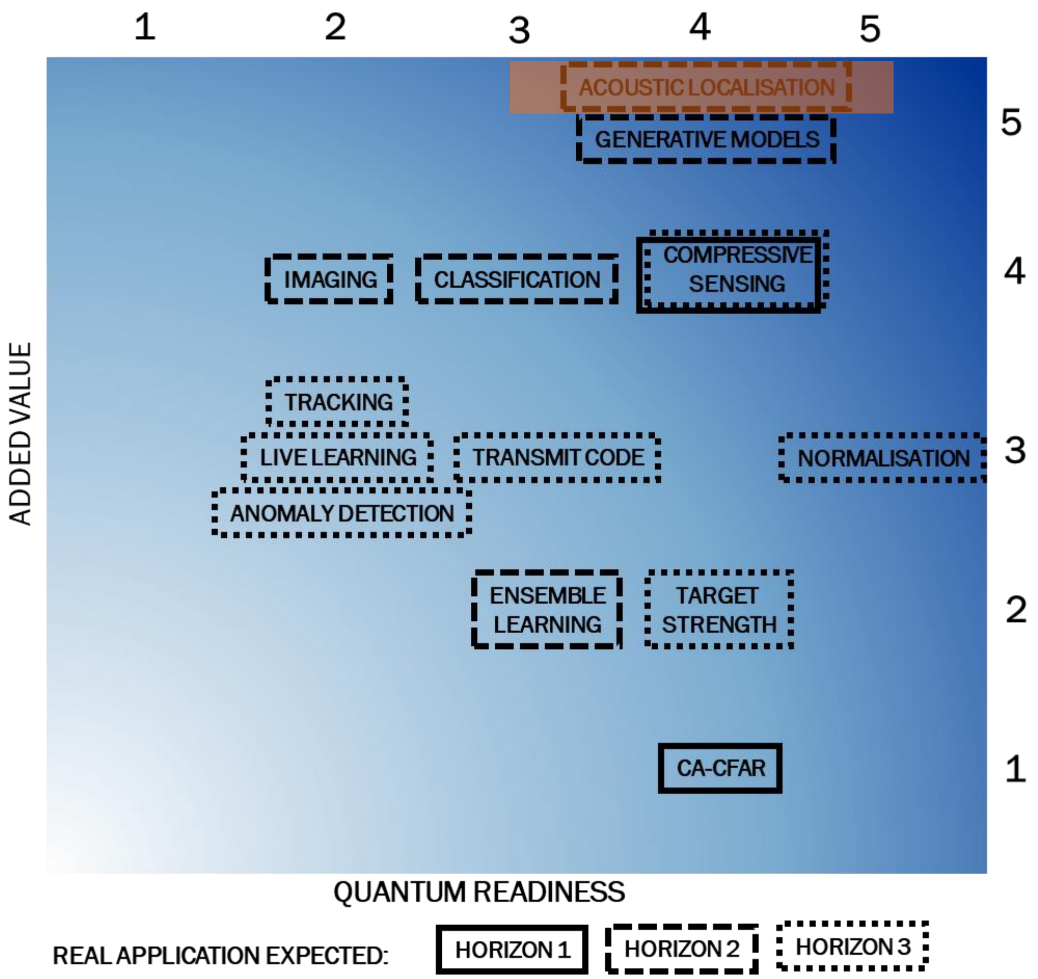


Can quantum computing offer this additional required computational power?

Potential applications Quantum computing

Quantum computing for radar and sonar information processing

Tariq H. Bontekoe et al., SPIE, 2022,
DOI: 10.1117/12.2618281



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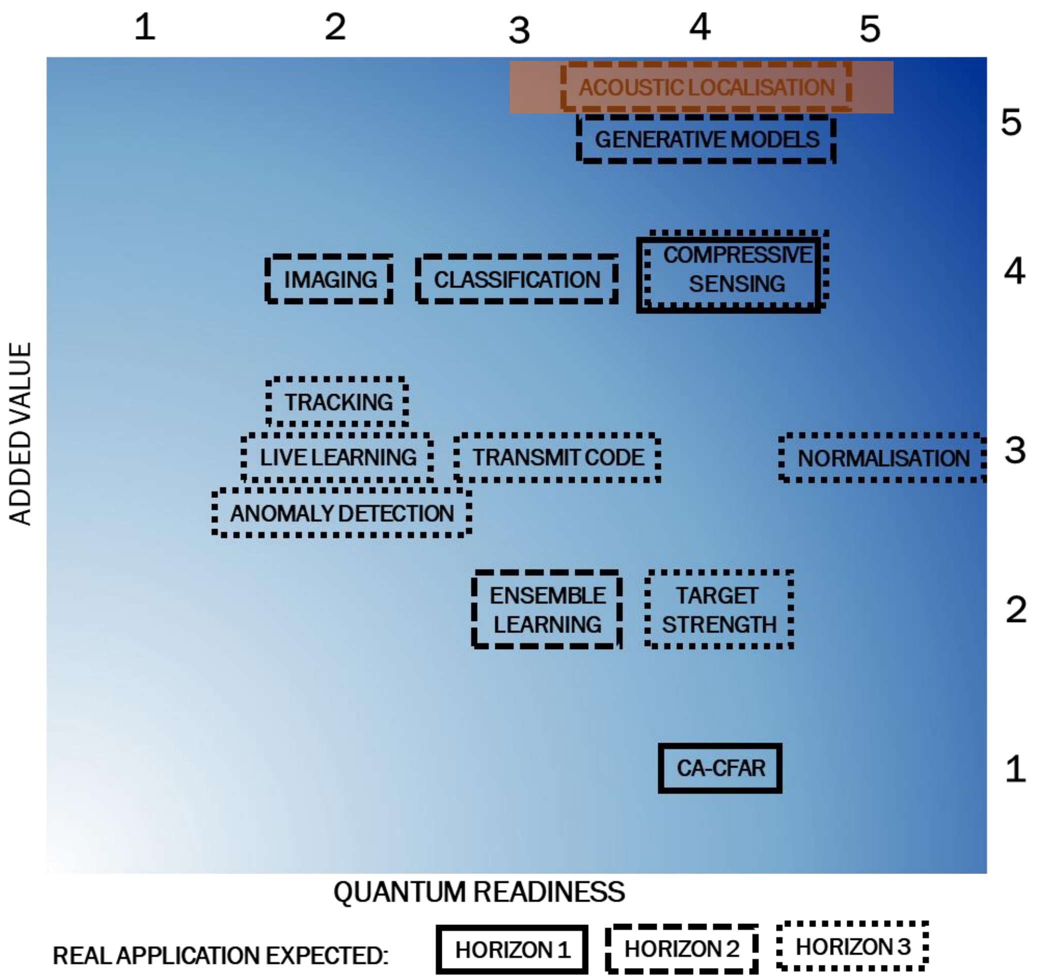
1. **Quantum Readiness** – Scale: 1-5
   - To what extend is the problem suitable for obtaining a quantum advantage?
2. **Added Value – Scale:** 1-5
   - What is the added value for the defence community to solve the problem faster, better or more effective?
3. **Horizon – Scale:** 1-3
   - When do we expect to run a real sized problem on quantum hardware?



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Enhancing model based acoustic localisation using quantum annealing

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ABSTRACT

In model based acoustic localisation (MBAL) the locations of underwater objects are estimated by comparing sensor measurements with model predictions. To obtain high quality predictions, computationally demanding propagation models need to be run for a large set of environmental parameters. The computational resources that are available onboard are typically not sufficient to perform accurate MBAL estimations on real-time data. In this work, we develop a quantum algorithm that uses quantum annealing to enhance underwater acoustic localization.

A restricted Boltzmann machine (RBM) is trained to predict the probability distribution of the candidate location of an underwater target. Advantage of this approach is that part of the computation can be moved to offline-training. Moreover, once the model is trained, the probability distribution can be sampled more efficiently using a quantum annealer. Potentially, this could enable real-time accurate target estimations to be made onboard. The RBM is applied to a simplified multi-sensor horizontal localization problem where we assume a constant and linear acoustic propagation. Using simulated annealing we show that the RBM is able to learn probability distributions that resemble target locations. First results show that the training and sampling can be done using quantum annealing hardware by D-Wave Systems for a limited size example.

Our contribution is the first work that explores how quantum algorithms can be applied for more efficient information processing for acoustic underwater localization.

1.0 INTRODUCTION

Underwater sensing is a key capability for navies. Various platforms, such as frigates, submarines, autonomous vehicles and underwater networks rely on passive acoustic monitoring to detect threats, or to navigate safely underwater. Passive localisation of objects in an underwater environment is a much more challenging task when compared to localisation on land [1]. Electromagnetic waves that are typically being used in air cannot be used in underwater settings as these waves dampen out too fast. Instead, acoustic waves are being used for underwater sensing. Underwater propagation of acoustic waves is far from trivial due to reflections off the bottom or surface and variable sound speed [2]. The exact propagation depends on many parameters such as depth, temperature, pressure and salinity of the underwater environment [3].

Model based acoustic localisation (MBAL) is the technique of localising an object in underwater environments by comparing acoustic sensor measurements to model output predictions of different candidate locations. Measurement errors, as well as uncertainties and variability in environmental parameters, for

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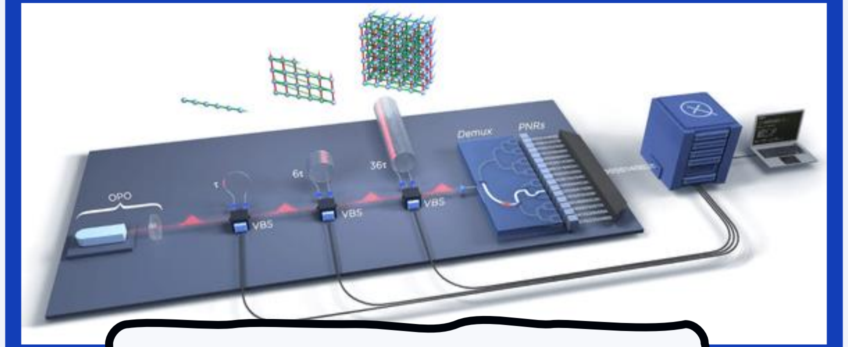
Various quantum computing paradigms

Gate-based quantum computers

QuTech, IBM, Microsoft, Google, Amazon

Annealing-based quantum computers

D-Wave



Photonic quantum computers

Xanadu, Quix

Various quantum technologies

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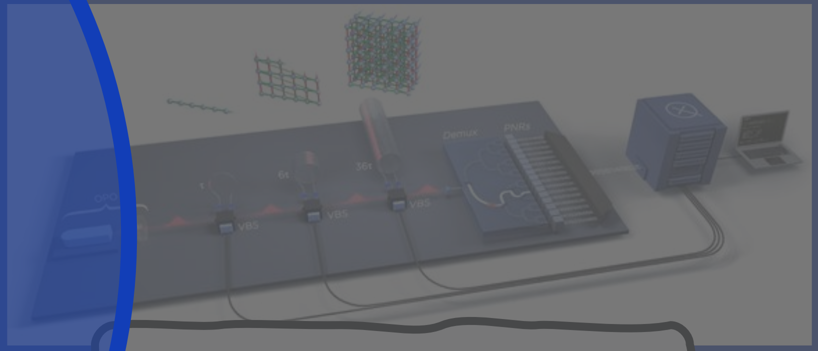

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quantum annealing

nologies

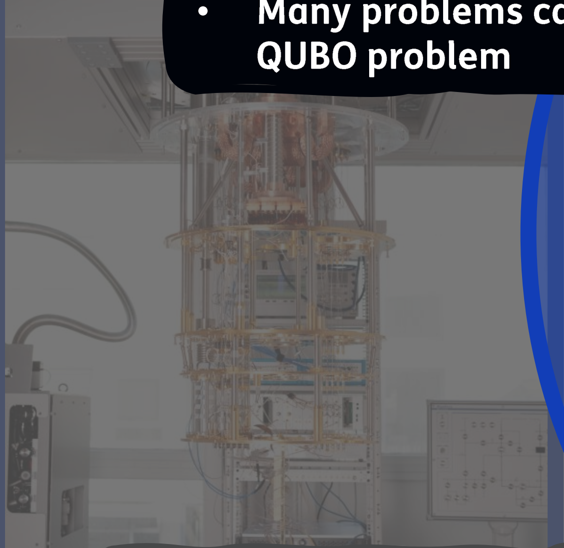
Solve specific type of optimisation problem:

QUBO

Quadratic Unconstrained Binary Optimisation

$$min\ \boldsymbol{x}^T Q \boldsymbol{x}\,, \qquad \mathbf{x} \in \{0,1\}^n, \mathrm{Q} \in \mathbb{R}^{n \times n}$$

- A QUBO problem is an NP-hard problem
- Many problems can be formulated as a QUBO problem



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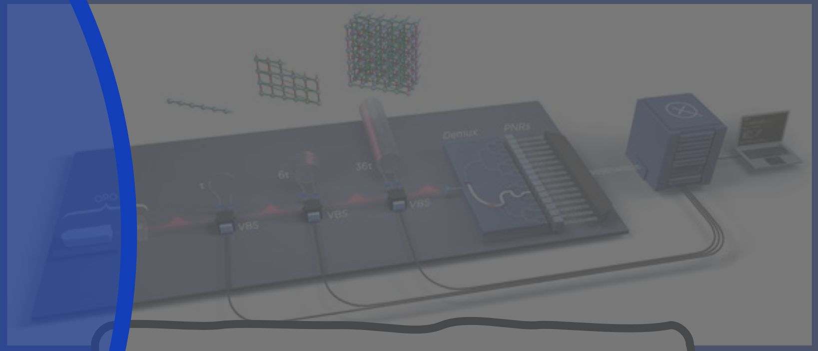

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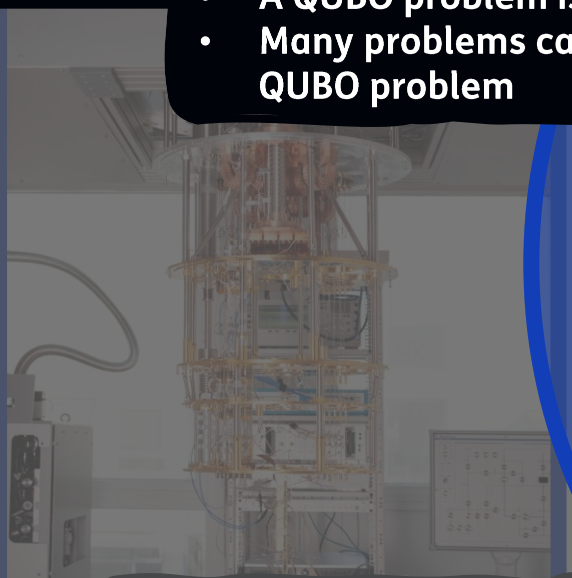
quantum annealing

Encode solution of QUBO as lowest energy state

Uses quantum properties such as:
- **Superposition**
- **Entanglement**
- **Quantum Tunnelling**

Annealing-based quantum computers

D-Wave



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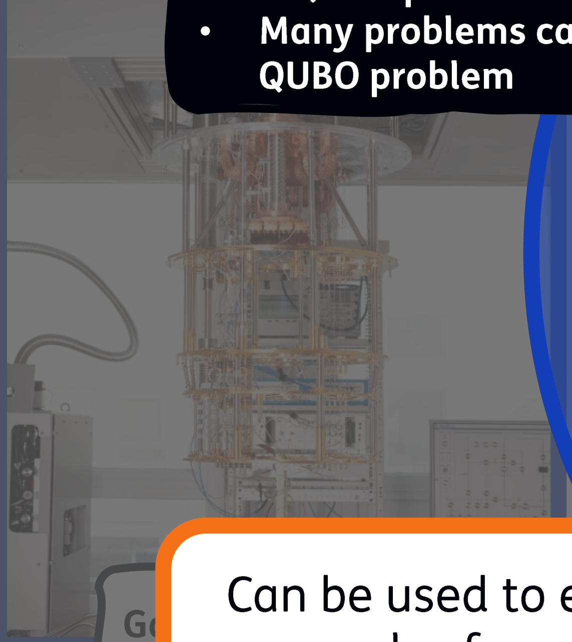

Annealing-based quantum computers

D-Wave

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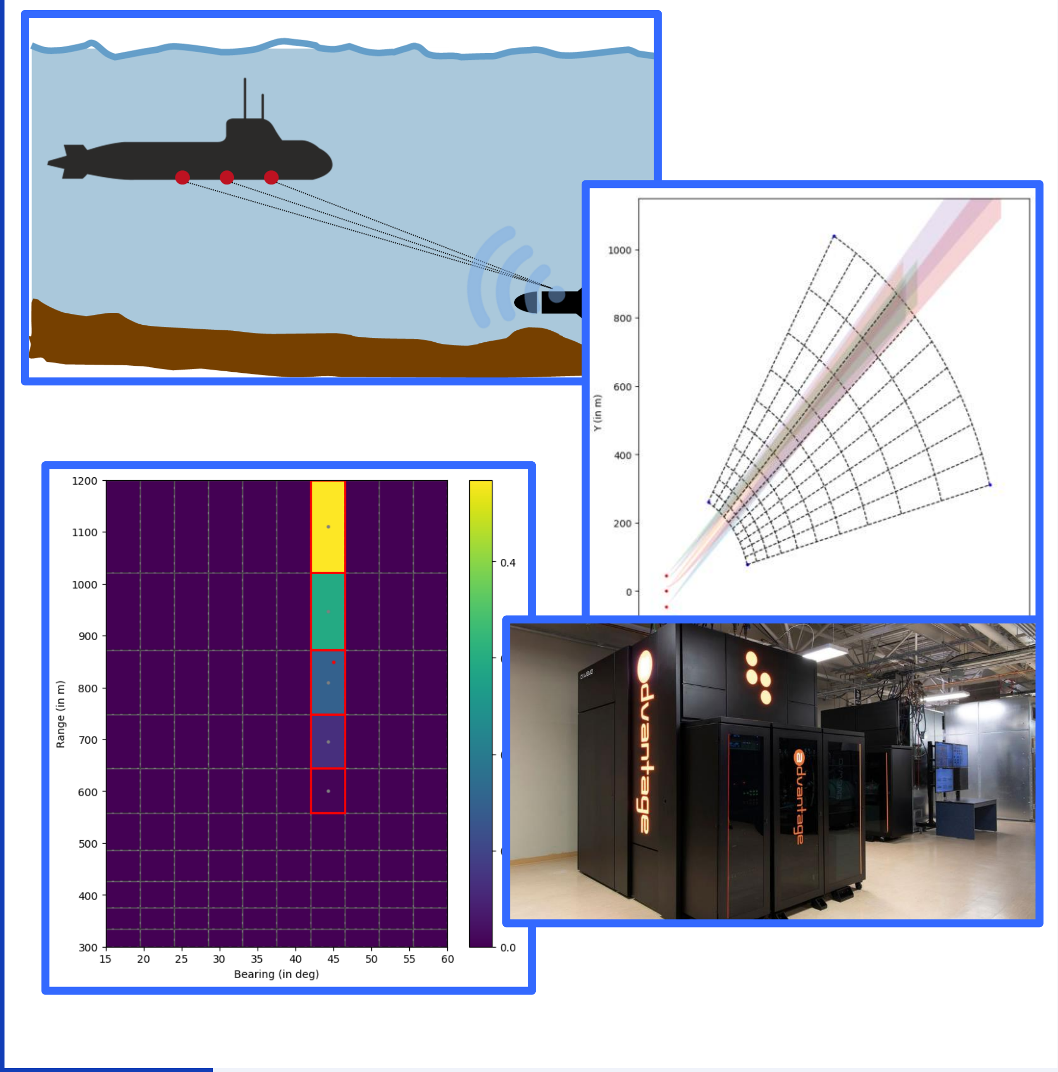
Can be used to efficiently draw samples from a Boltzmann distribution.

Problem modelling

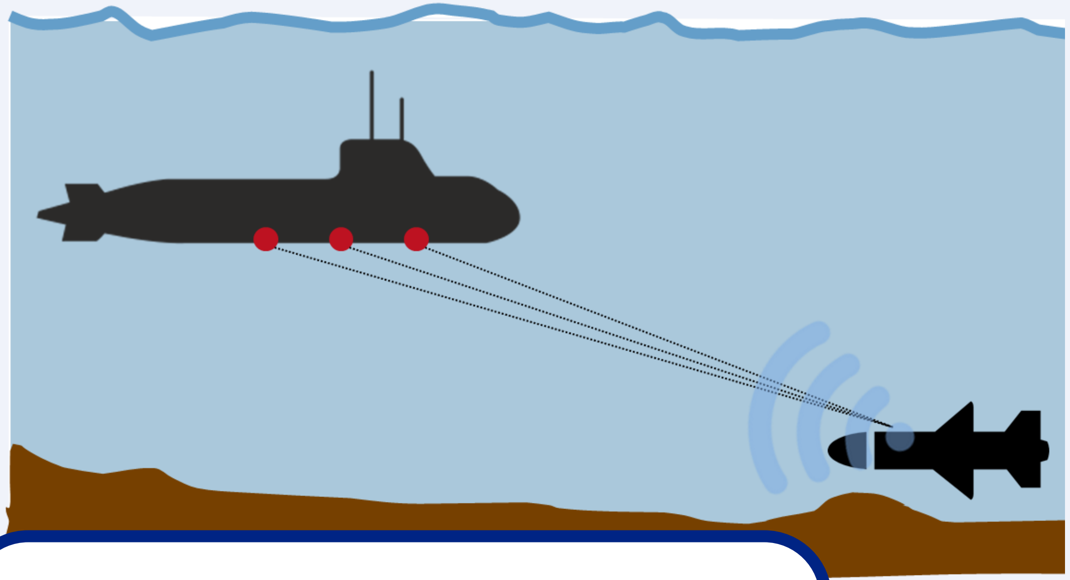
Remodel a **multi-sensor horizontal localisation problem** to a problem that can be solved using a quantum annealer.

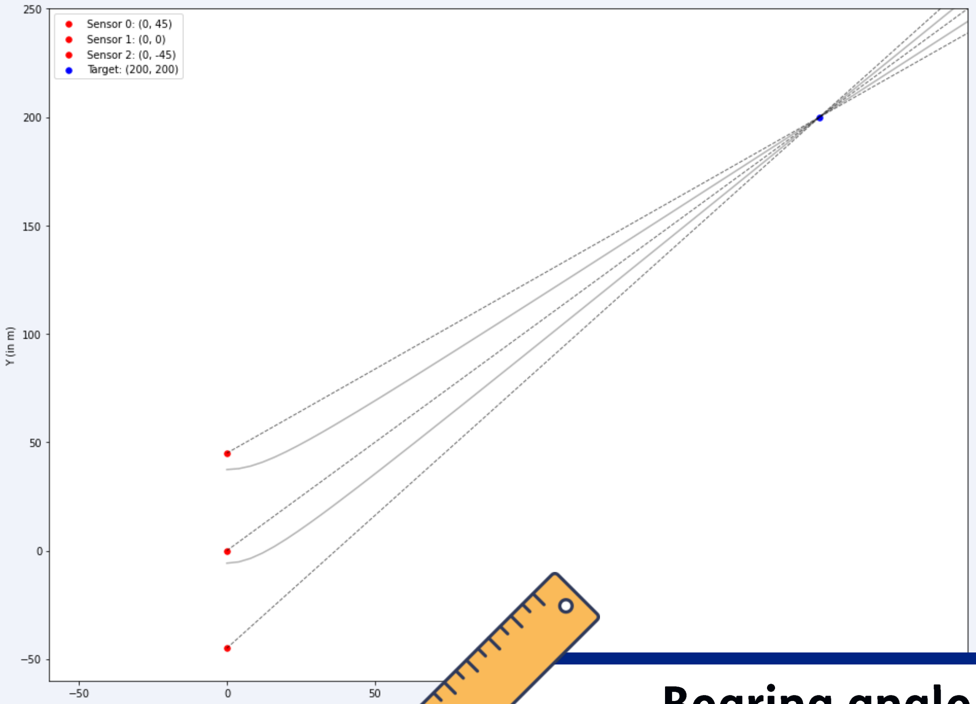
Supervised machine learning approach:

- Training the model can be done offline.
- Potentially, enable real-time accurate target estimations onboard once model is trained.
- *Limited size due to available number of qubits and binary variables.*



Simplifying assumptions

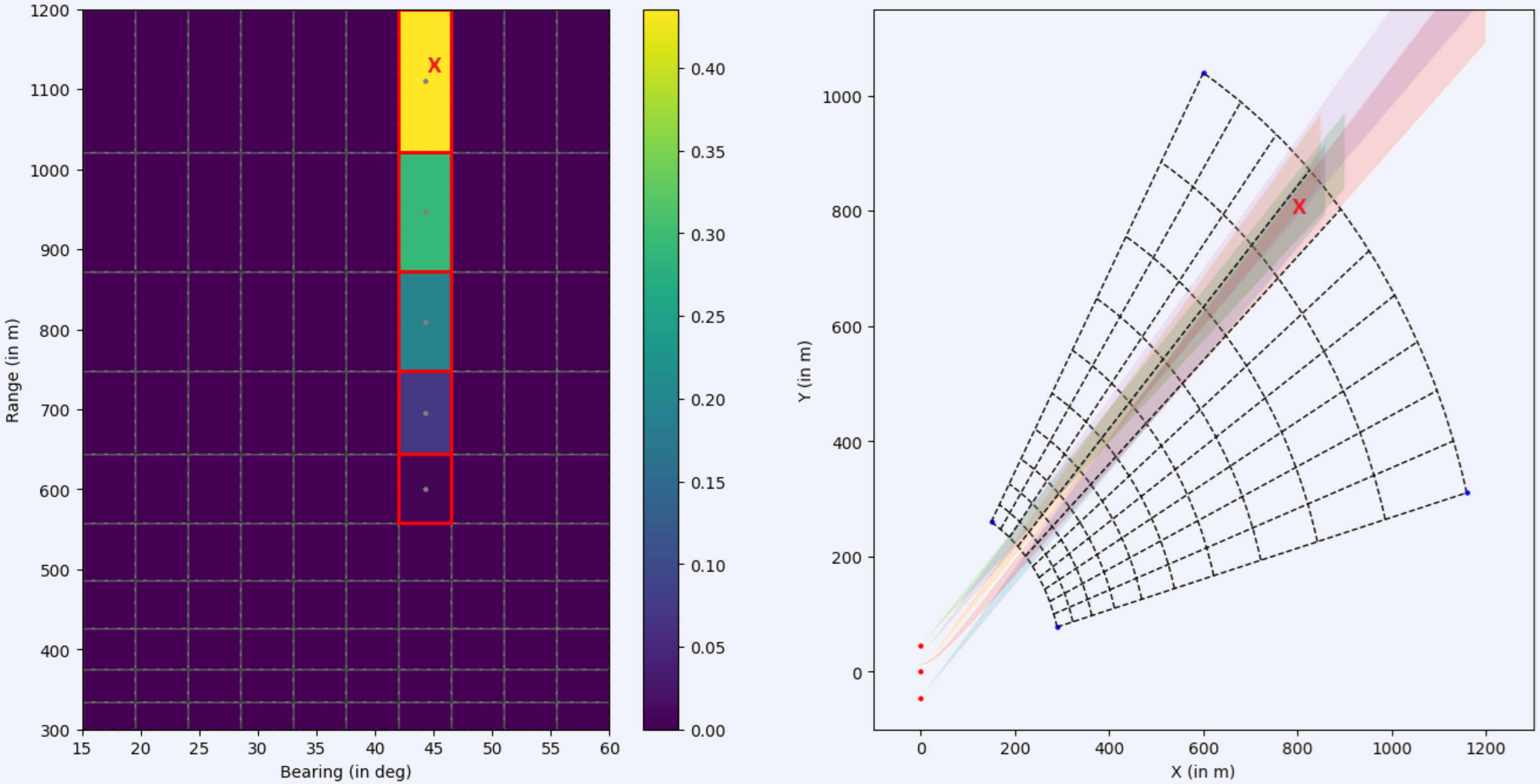




Assumptions:
- 3 sensors on submarine
- Sound propagates **linearly** with **constant velocity**

- **Bearing angle**
- Time difference of arrival **(TDOA)**

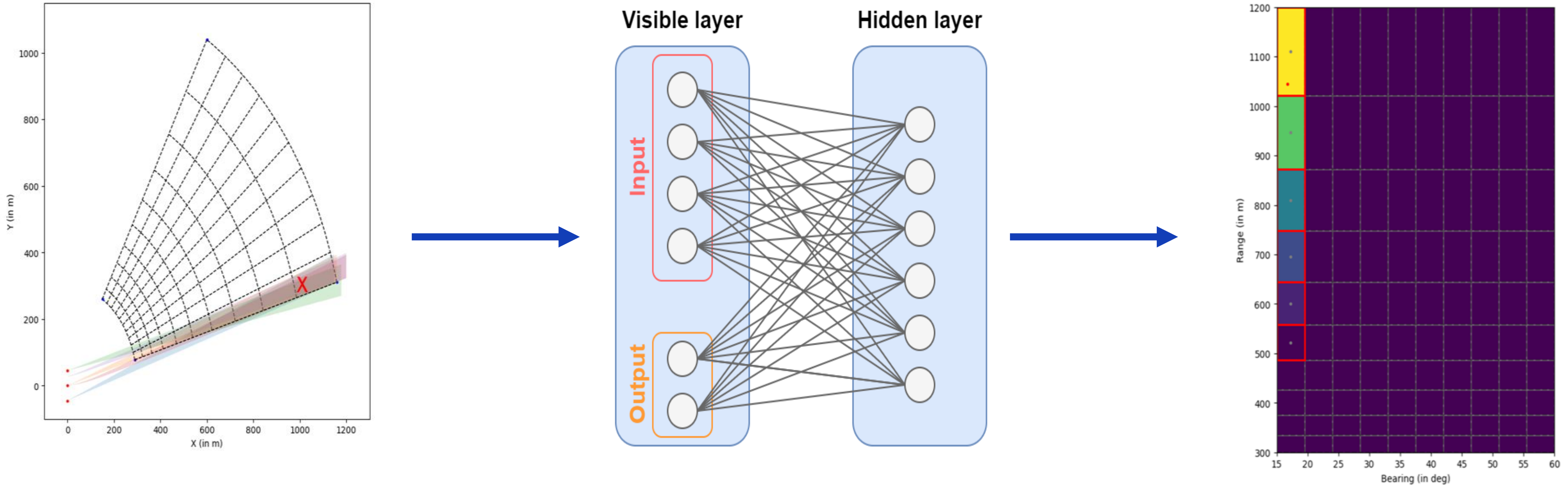
Discretisation of the problem space



Restricted Boltzmann machine

Restricted Boltzmann machine

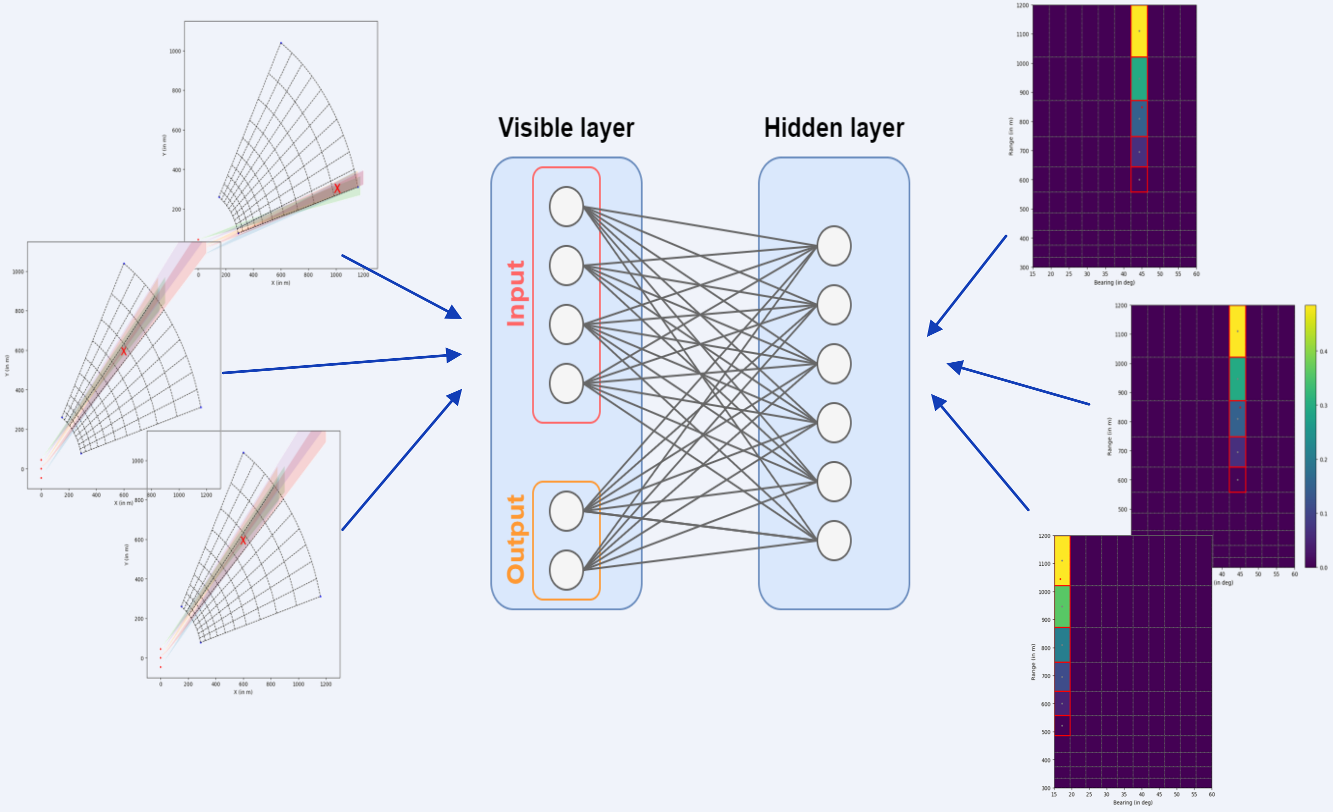
- ‘Neural networks’ used for generative machine learning (supervised learning)
- Offload computation from online procedure to offline procedure



Goal: learn probability distribution over set of inputs

Training the restricted Boltzmann machine

1. **Show many inputs + output distribution combinations to the RBM**
2. Update weights of the network
3. Hope that the RBM is eventually able to learn to predict output distributions



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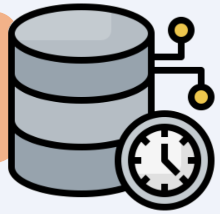

Drawback of restricted Boltzmann machine

Updating weights requires drawing samples from Boltzmann-like distribution which is a computational hard task!

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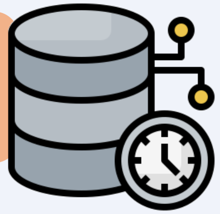

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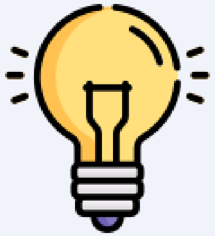

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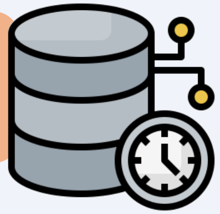

Drawback of restricted Boltzmann machine

Updating weights requires drawing samples from Boltzmann-like distribution which is a computational hard task!

- Utilize the **quantum annealer's** ability to generate samples from a Boltzmann distribution for training the RBM.
- As a cheaper alternative to study quantum annealing we use **simulated annealing.**

Training the restricted Boltzmann machine

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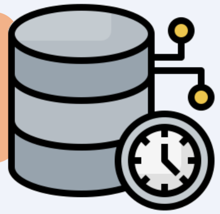
2. **Update weights of the network**



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- **Efficient training**
- **Efficient sampling**

Drawback of restricted Boltzmann machine

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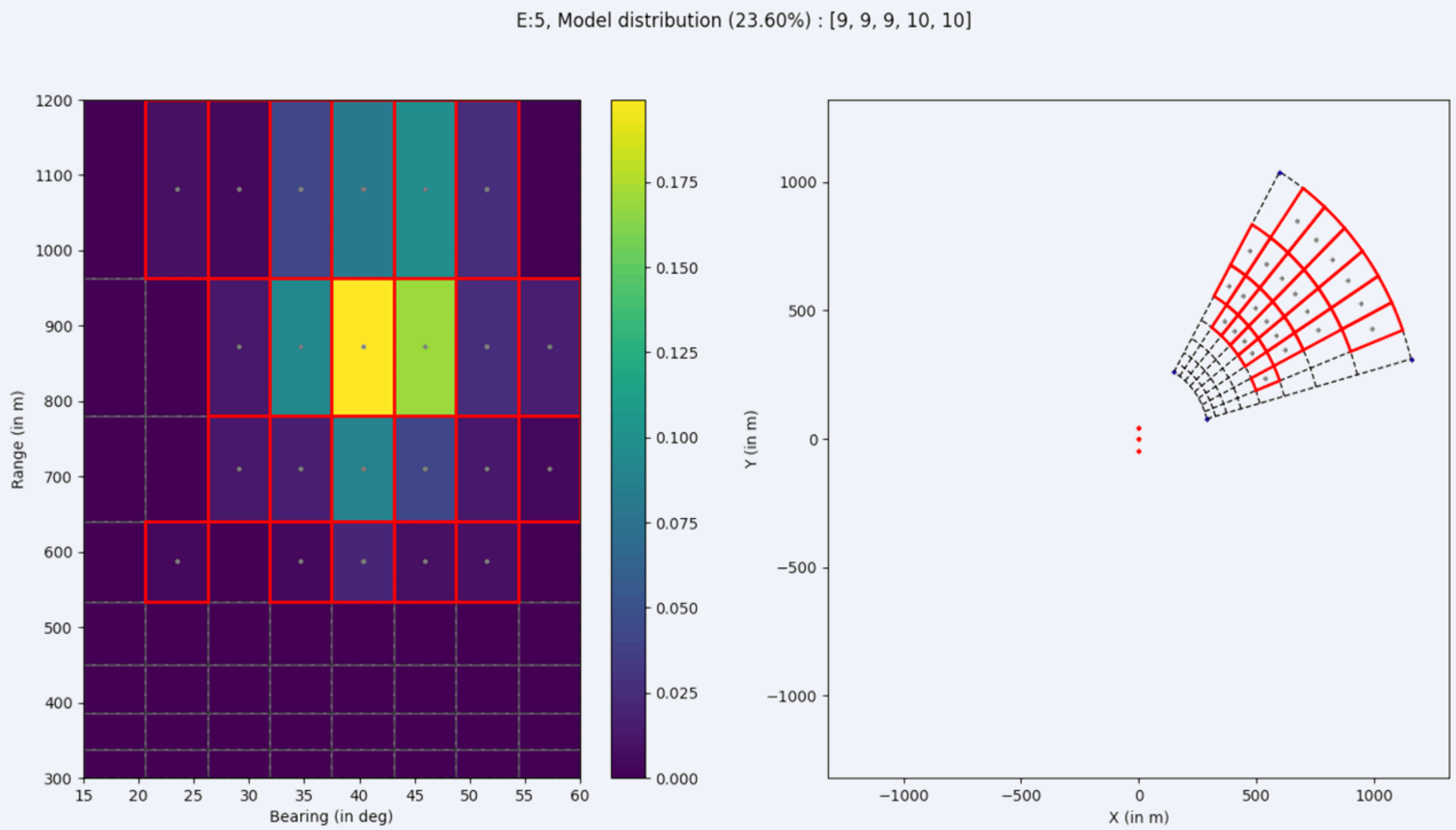
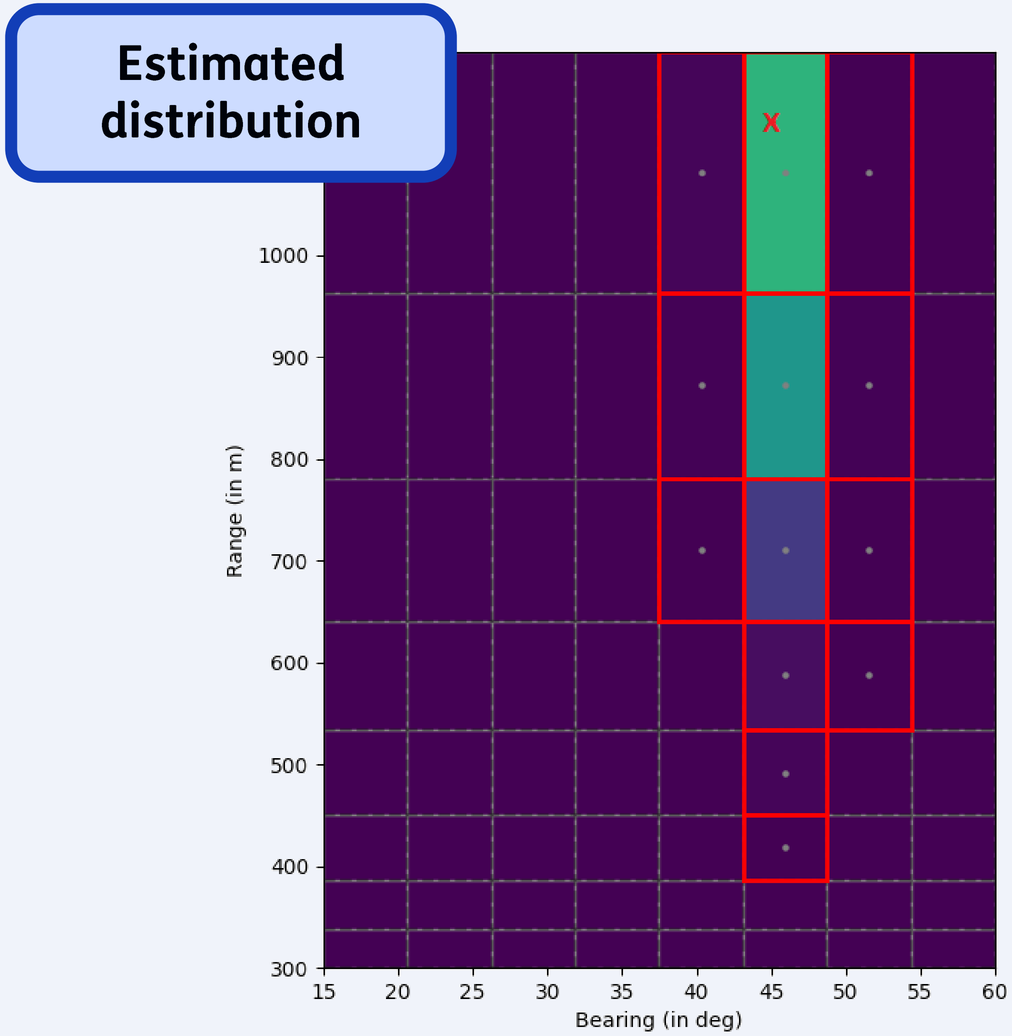
Example of training

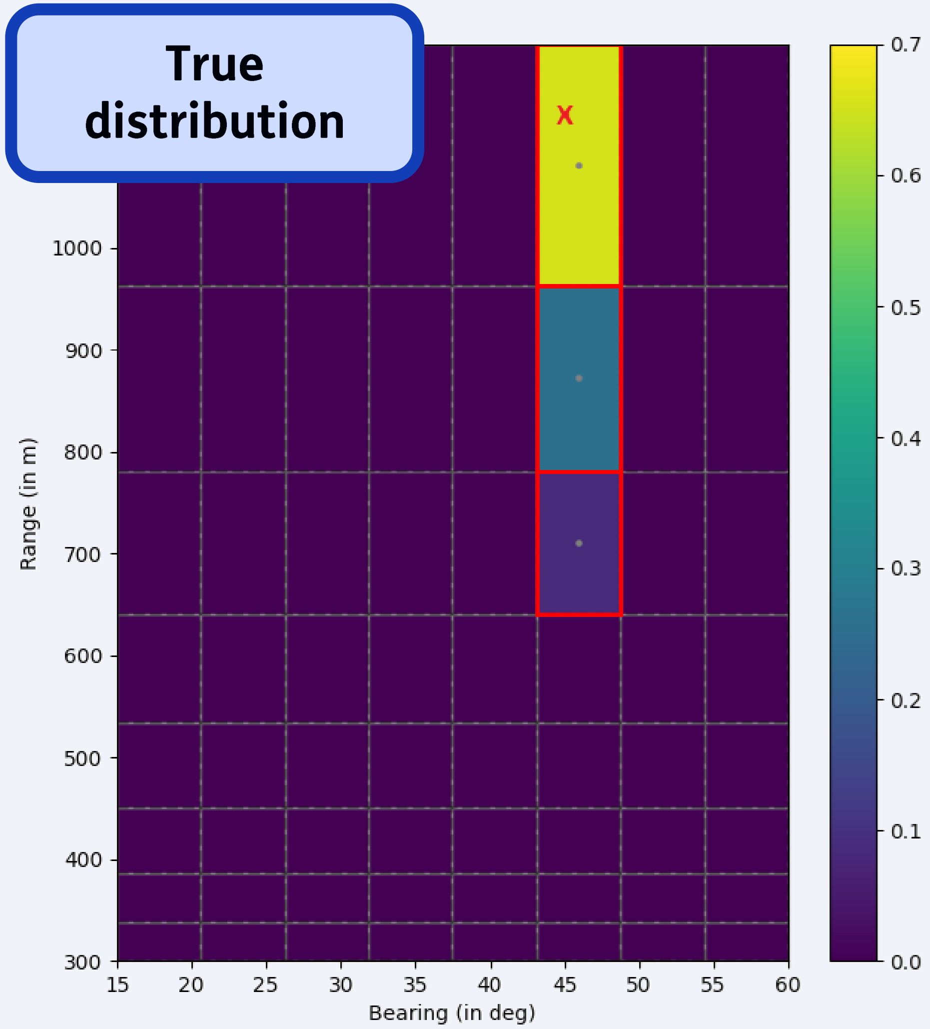


Simulated Annealing results

Example: Obtained probability distribution



Simulated Annealing result

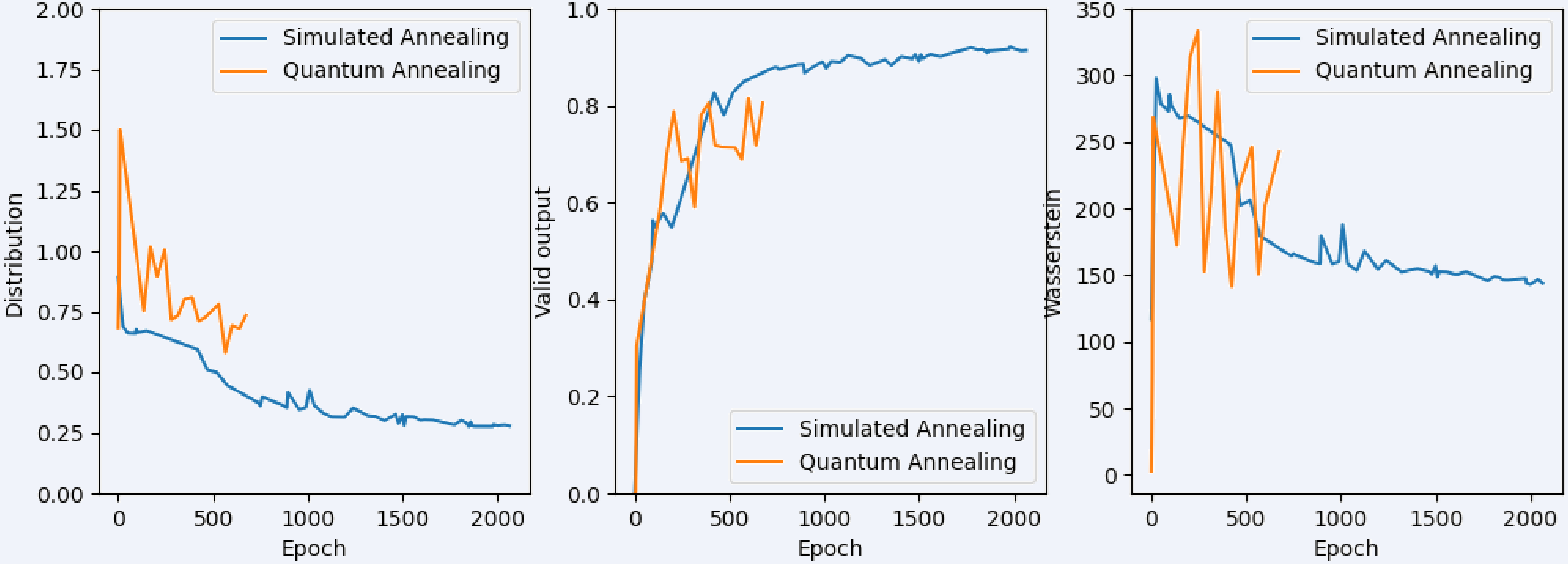


Measures of performances

Distribution
Compares distribution of the environment and the distribution from the *valid* outputs
Range: [0, 2]
Optimal result: 0

Valid output:
% of output samples with correct output format
Range: [0, 1]
Optimal result: 1

Wasserstein distance
How much work does it cost to transform one distribution into the other distribution
Range: [0, inf]
Optimal result: 0



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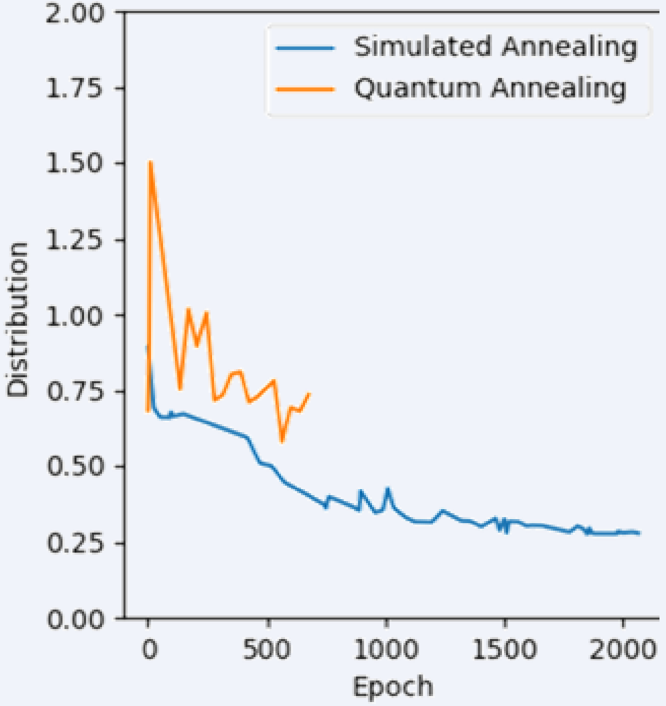
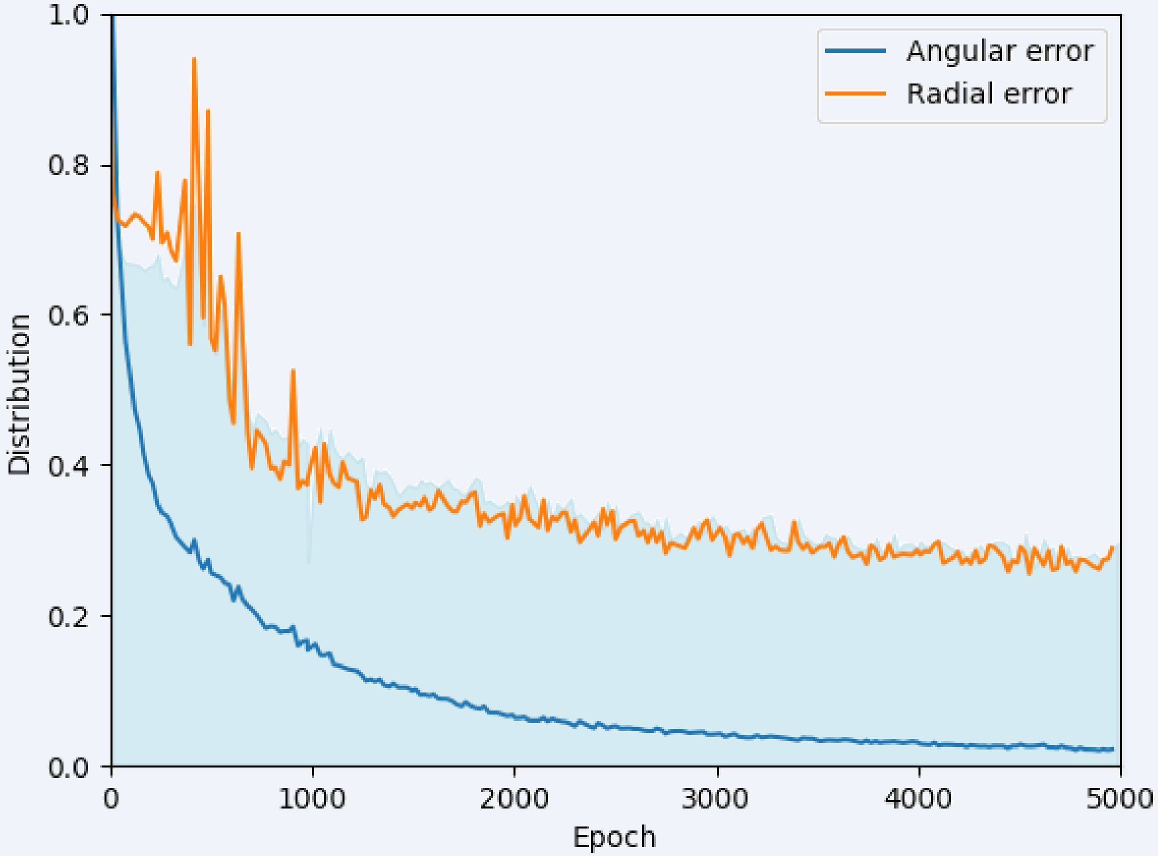


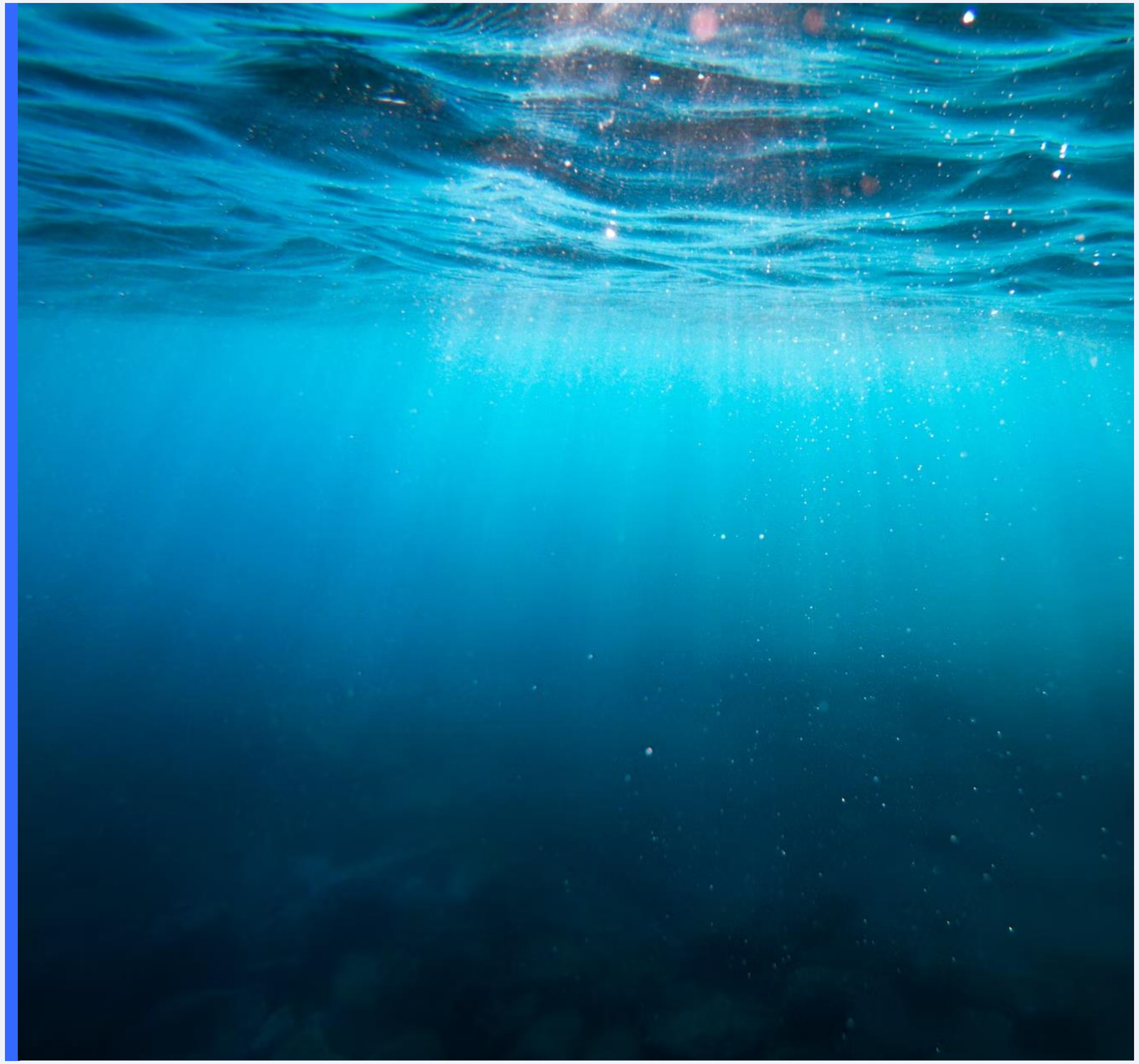


Simulated Annealing result

Conclusions

Benefits RBM approach:

- Training of the model can be done offline
- Sampling can be done in real-time onboard
- QA can potentially improve training and sampling.



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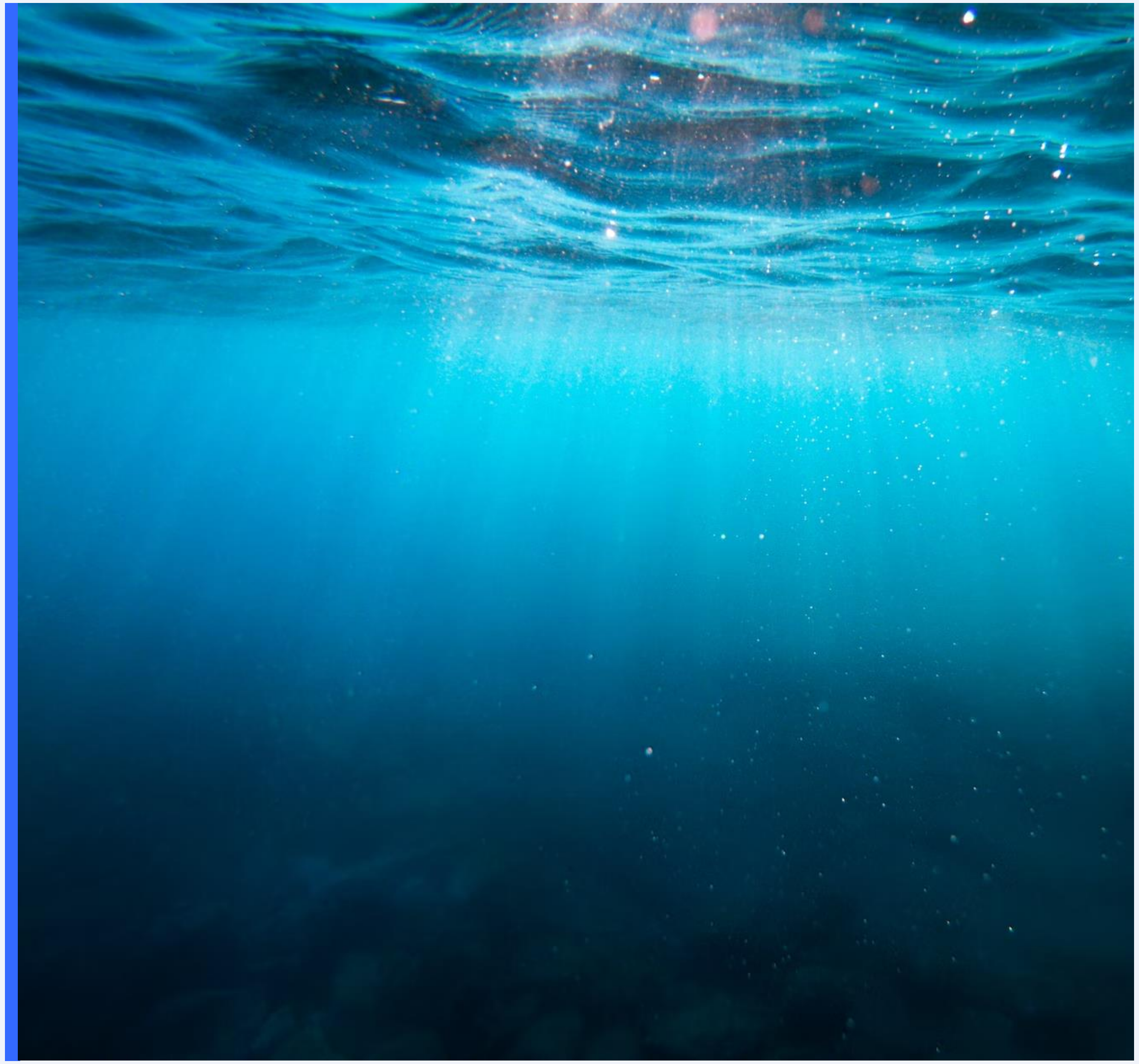
Current performance

- RBM is able to the learn angular dependency well.
- Challenges remain in the radial dependence.
  A common problem in acoustic localisation.
- Current hardware size restrict us to small toy problems.



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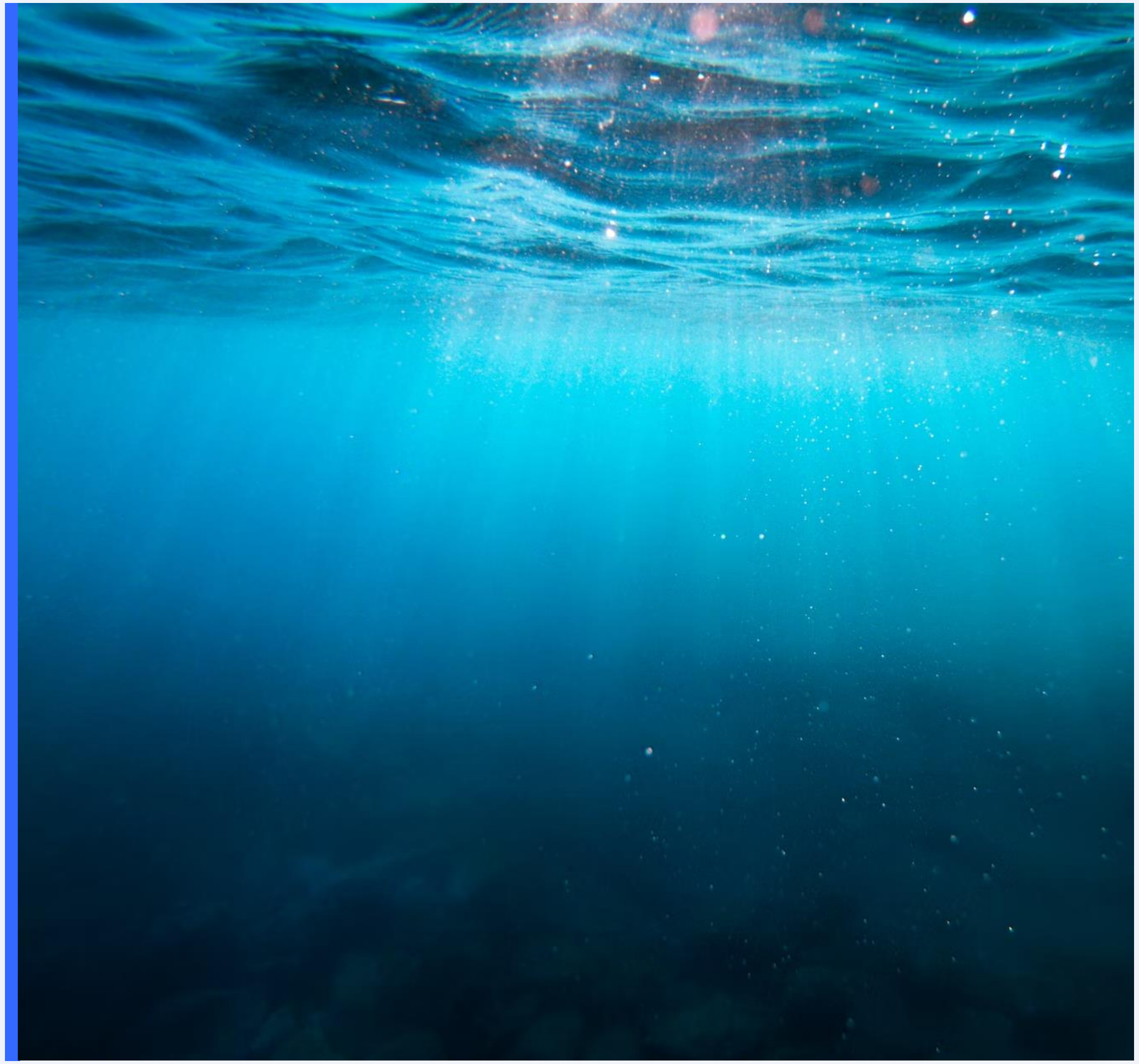
Next steps

- Comparison with RBM that is trained with conventional techniques.
- Increase complexity of the underwater environment.



Questions & Contact information

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