

# The role of artificial intelligence in geophysics: current and future

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# Outline

## Part I: What is AI ?

- Knowledge bases system
- Learning from experience and data
- Supervised, unsupervised learning
- Basics of deep learning

## Part II : Current applications of AI in geophysics

- Why is AI relevant to geophysics?
- Seismic processing and interpretation
- Supervised ML
- Clustering
- Generative models

## Part III: Perspectives of AI in geophysics

- Data collection with autonomous vehicles
- Physics-informed neural networks
- The inverse problem
- Fast machine learning
- Getting rid of the non-uniqueness curse?

## Conclusions

The background of the slide is a soft-focus, abstract illustration of a neural network. It features several glowing, yellowish-orange spherical nodes connected by thin, translucent, wavy lines that resemble axons or dendrites. The overall color palette is a mix of light pinks, purples, and greys, creating a futuristic and organic feel.

**What is artificial intelligence (AI) ?**

# What is artificial intelligence?

- ***“AI, or Artificial Intelligence, refers to the development of computer systems that can perform tasks that typically require human intelligence.”***

*ChatGPT-3.5*

- ***“AI leverages computers and machines to mimic the problem-solving and decision-making capabilities of the human mind”***

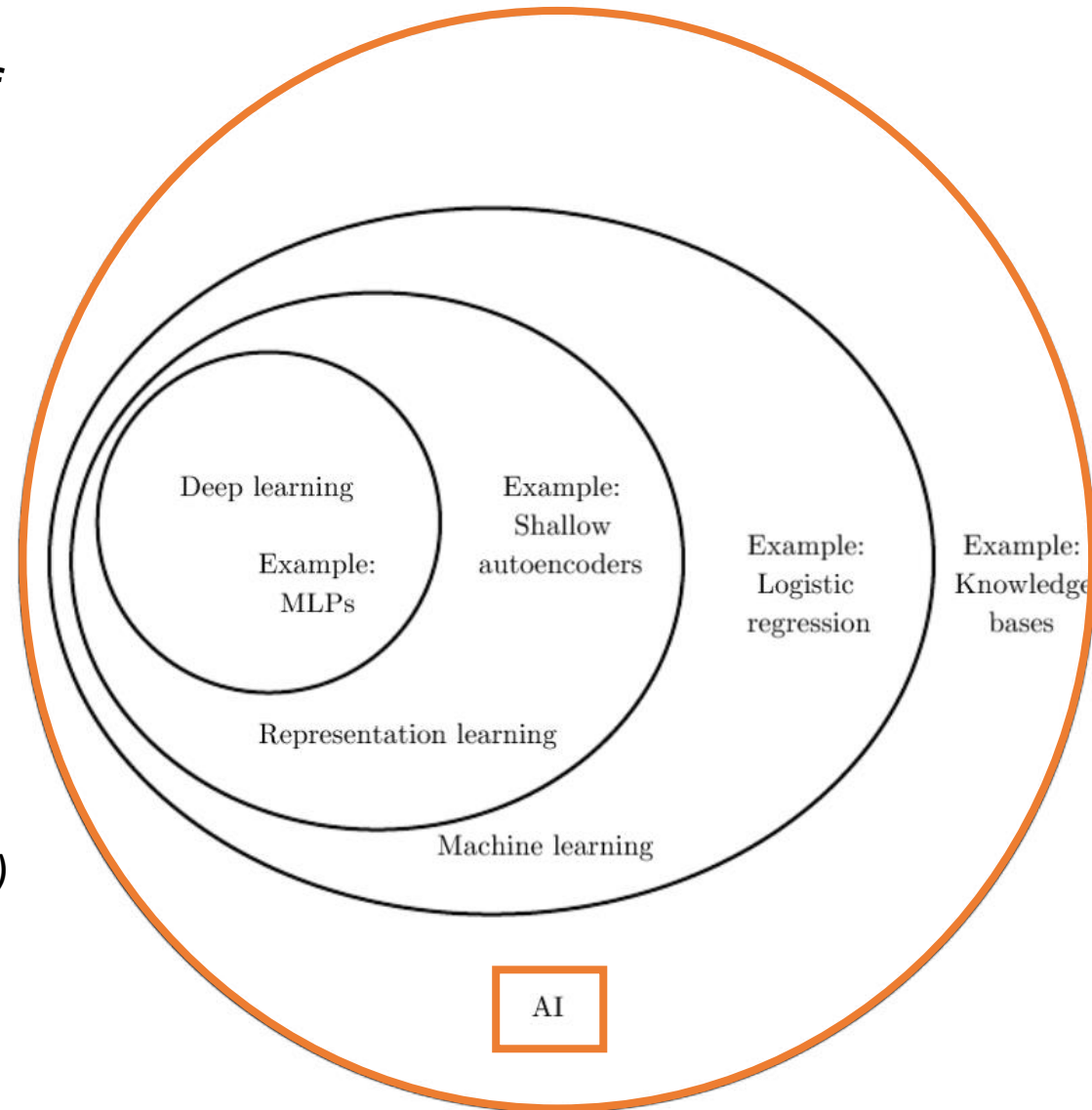
*IBM*

- ***“relevant to any intellectual task; it is truly a universal field”***

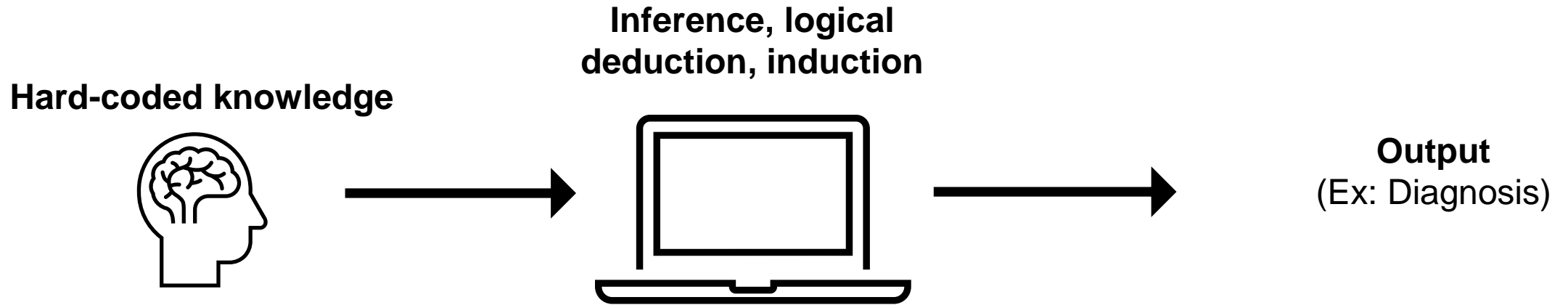
*Russel and Norvig (Artificial Intelligence, A modern approach)*

- ***“in the long run, AI is the only science”***

*Woody Bledsoe*



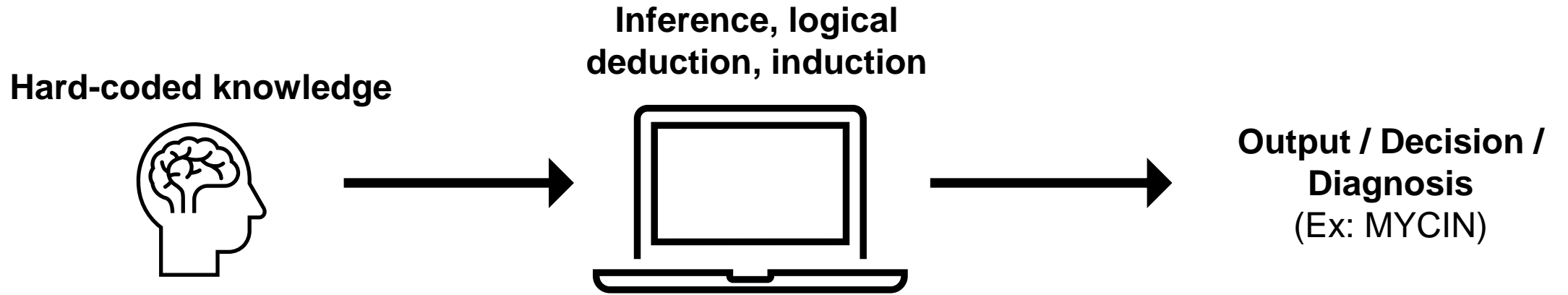
# Knowledge bases system



**Algorithm are based on hard-coded knowledge, set of mathematical rules, axioms:**

- Ex: IF the patient has a fever AND the patient reports chills AND the patient has a positive blood culture for bacteria X THEN the diagnosis is likely bacterial infection caused by bacteria XCF (Certainty Factor) = 0.8
- Rules of a chess game
- Intellectually difficult for humans but relatively easy for computers

# Knowledge bases system



## Limitations

- How to set up hard-coded rules for object or speech recognition?
- The most intuitive tasks for human beings are difficult to represent by a set of rules
- The challenge is to represent the expertise of human specialist accurately

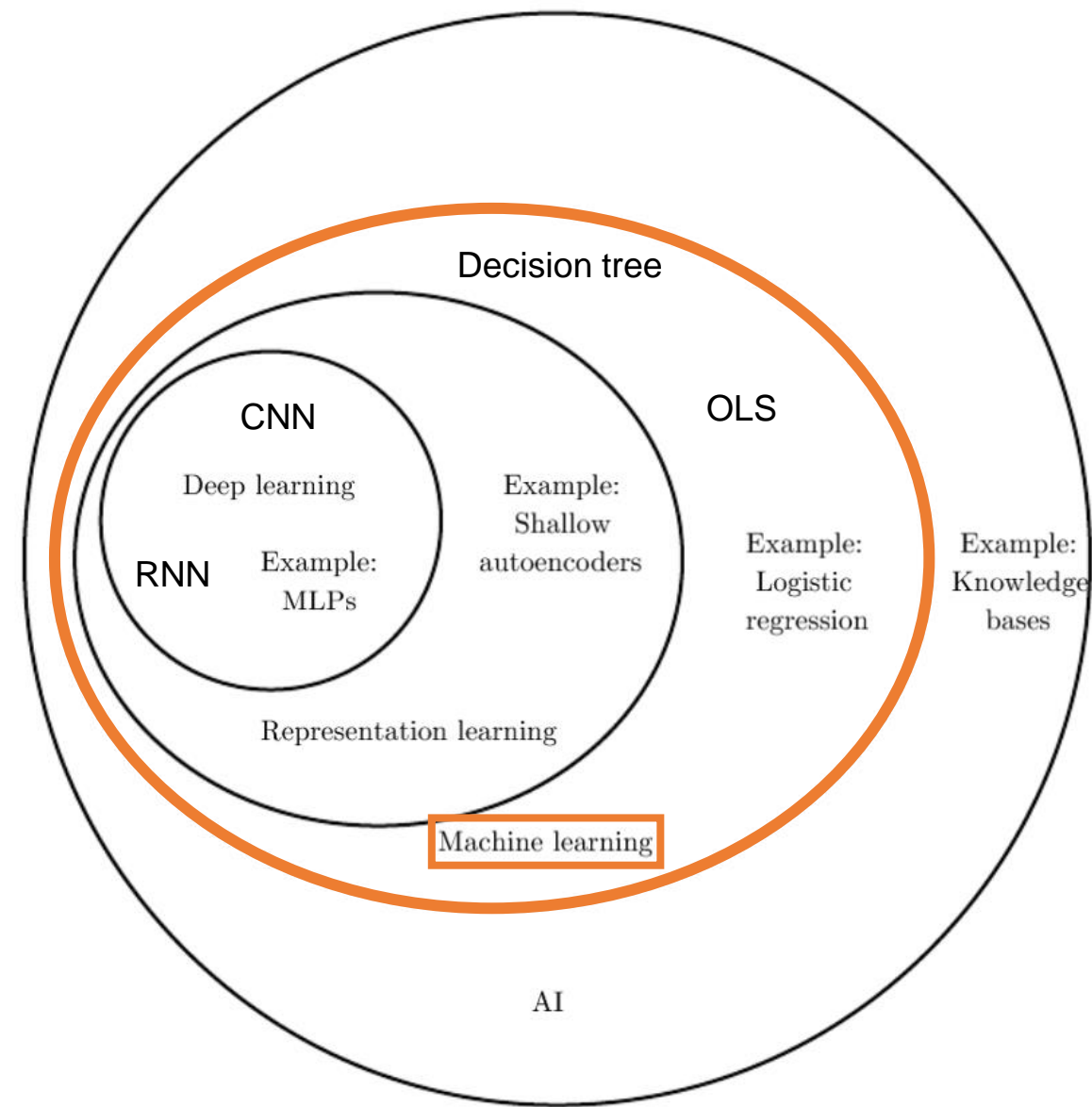


# What is machine learning?

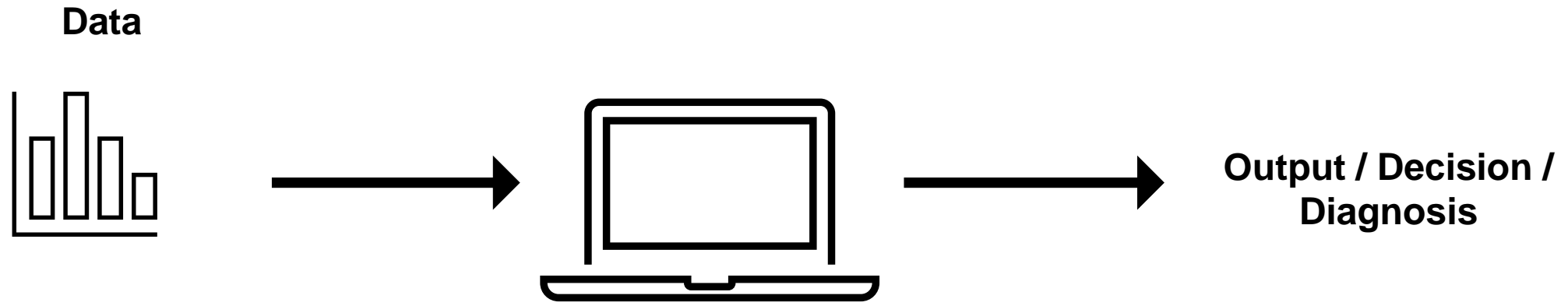
- Definition: Machine learning is a set of techniques that enables **computer systems** and algorithms to **improve** with **experience** and **data**
- Nowadays, AI is pretty much about **Machine Learning**

*“Learning is fueled by knowledge, and human-scale learning demands a human-scale amount of knowledge”*

*Douglas Lenat (1989)*



# What is machine learning?



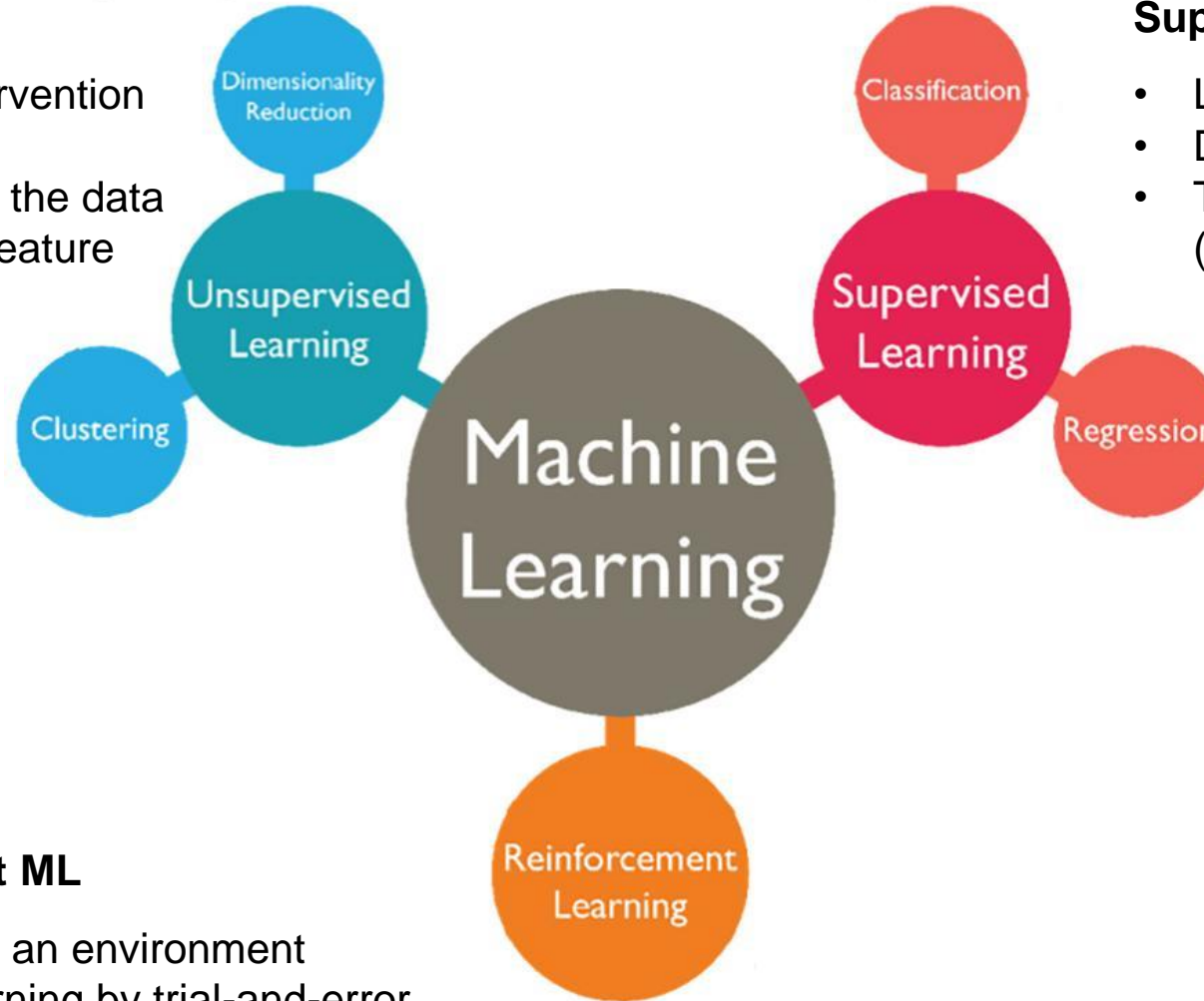
- A plethora of techniques and tools
- Ordinary least square, logistic regression, decision tree, clustering, feed-forward neural networks
- For both regression and classification tasks



# What is machine learning (ML) ?

## Unsupervised ML

- Does not require human intervention or labels
- Find patterns and features in the data
- Learn the representation or feature itself



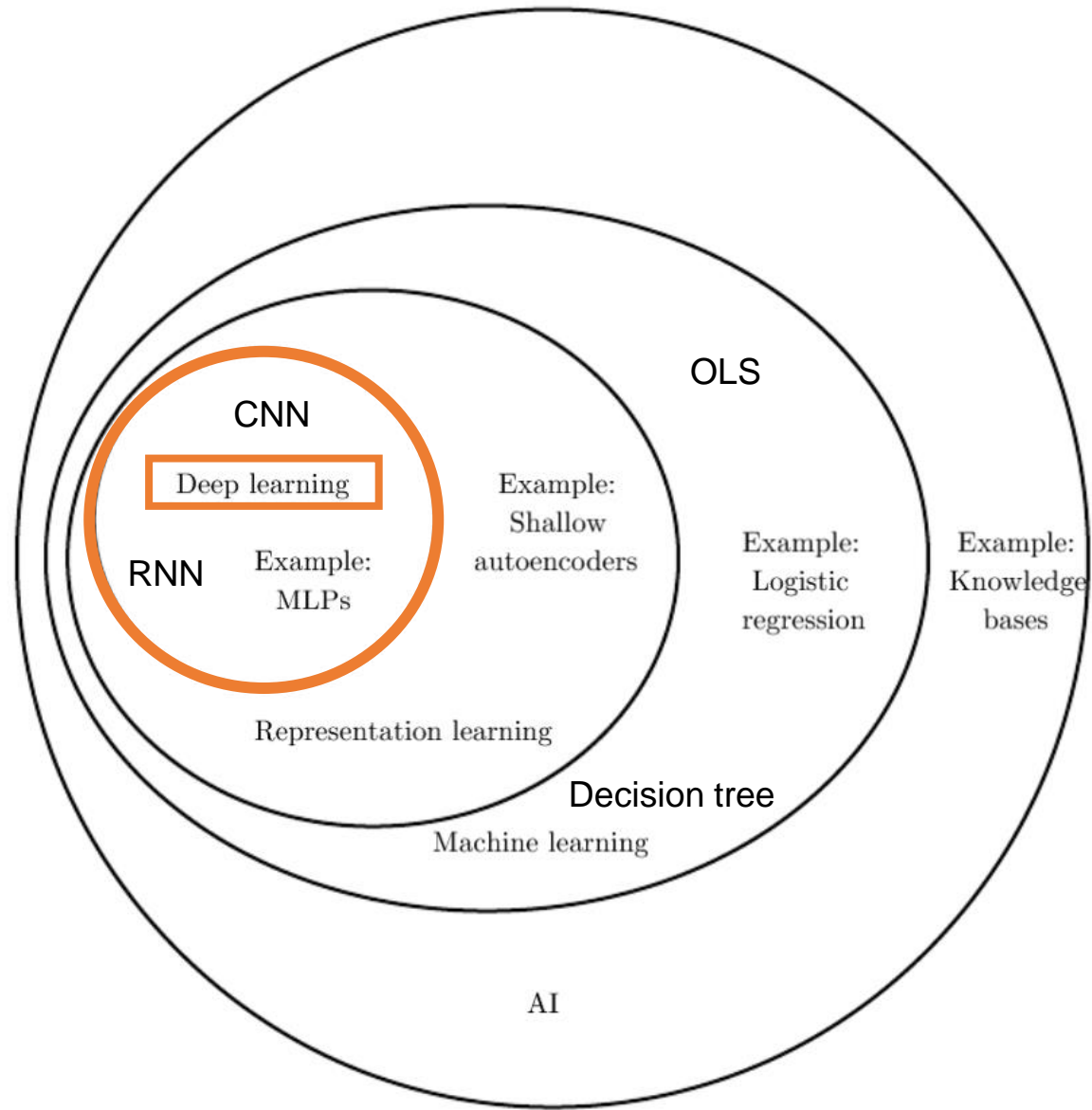
## Supervised ML

- Labelled data by humans
- Data greedy
- Take decades to build labelled datasets (ImageNet)

## Reinforcement ML

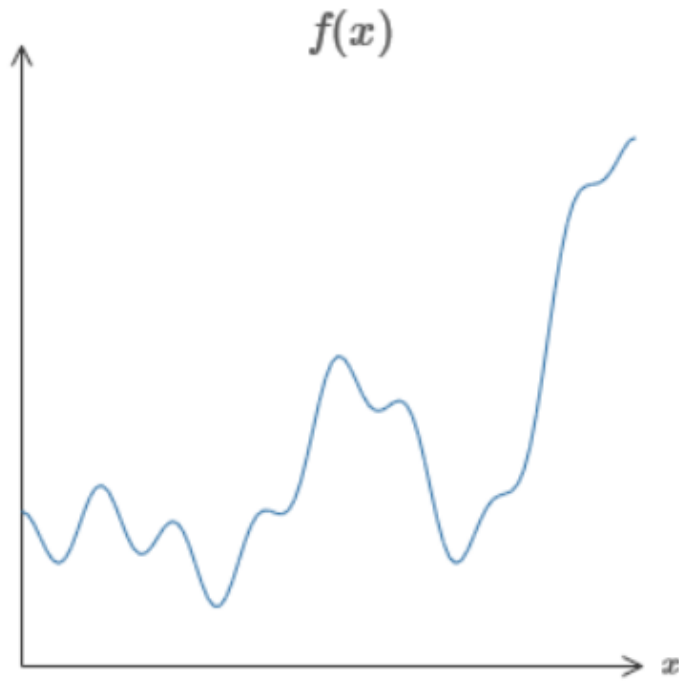
- Interact with an environment
- Achieve learning by trial-and-error
- Policy is adapted according to reward and punishment

# What is deep learning (DL)?

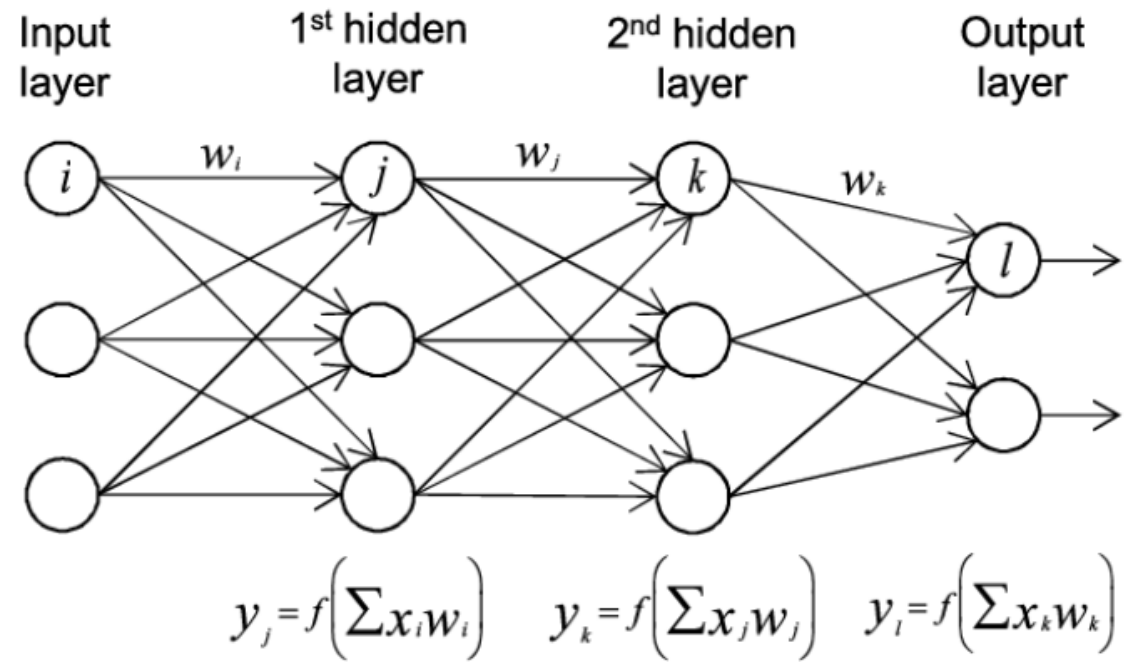


# Basics of deep learning

*Universal approximation theorem:* a **feed-forward neural network** with just a single hidden layer containing a finite number of neurons can approximate **any continuous multidimensional function** to arbitrary accuracy.



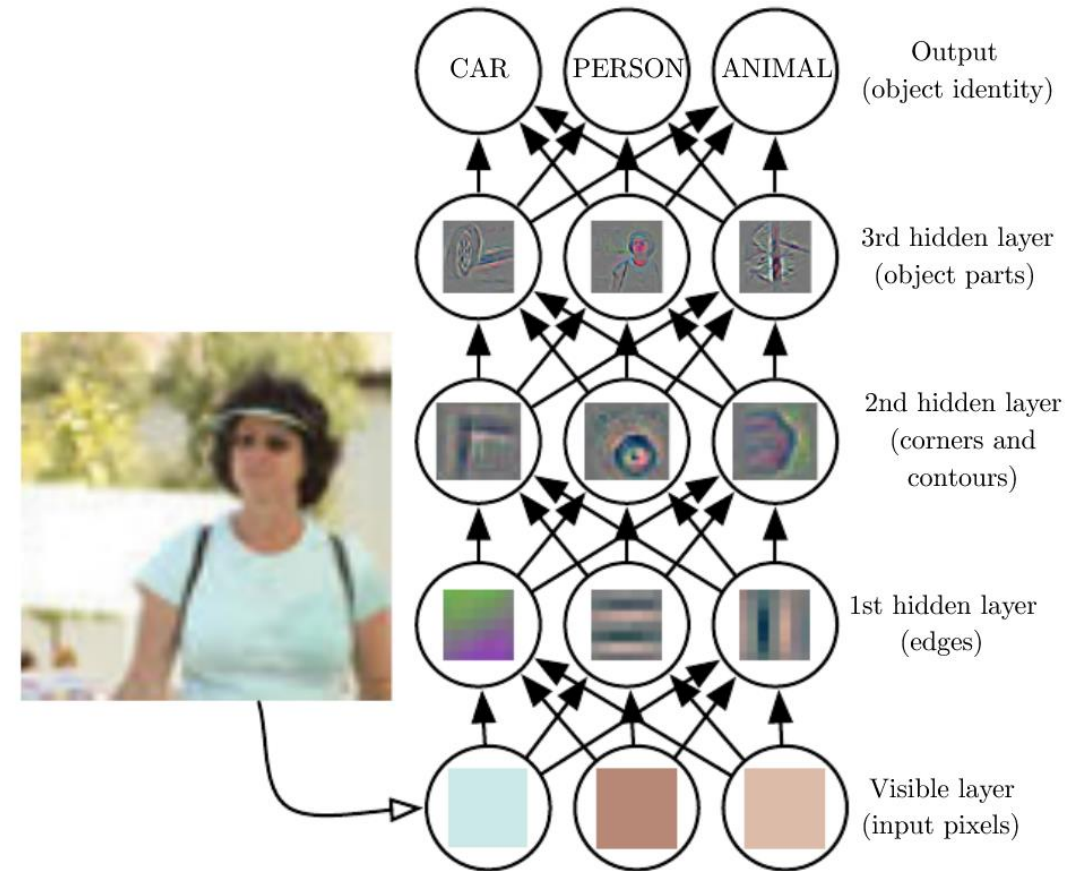
## Artificial neural network with 2 hidden layers



# Basics of deep learning

- During training, neural network **weights** and **biases** are updated with the **backpropagation algorithm**
- The **depth** of the neural network is the number of hidden layers, hence **deep learning**
- Neural networks is the predominant **programming paradigm** in AI, capable of learning complicated tasks like **pattern recognition**
- There are a **plethora** of deep learning algorithms: CNN, RNN, GNN, ANN, PINN, autoencoders, etc.
- Active research in DL are narrowly linked to advances in the field of **mathematical optimization**

## Neural networks with 3 hidden layers





# **Current use of AI in geophysics**

# Why is ML relevant for geophysics?

- Like any other natural sciences, **geophysics** relies heavily on **observations**
- Modern geophysics is **computationally-intensive** and advances ML are often important in optimization of calculations and data storages
- Any advances in **optimization** techniques with ML can be applied to **objective functions** in **geophysical inversion**
- In this trial lecture, we will focus on **solid earth geophysics**



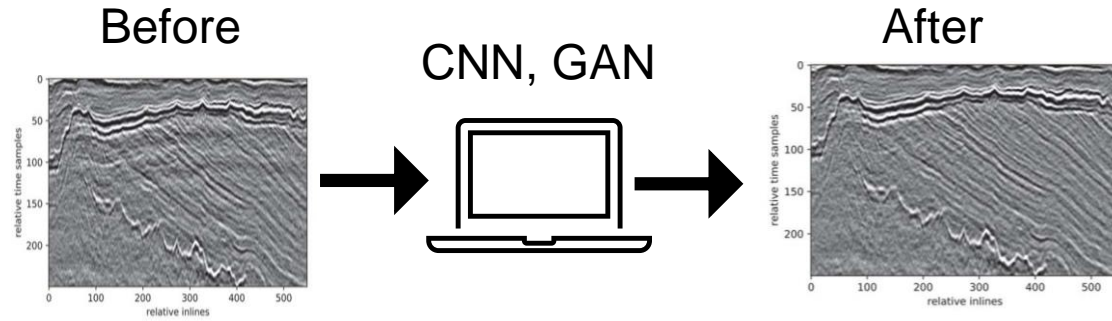
*“Since the fundamental task of optimizing an objective function is also central to modern machine learning efforts, recent geophysical studies have also sought to exploit advances from that sphere.”*

*Valentine and Sambridge (2023)*

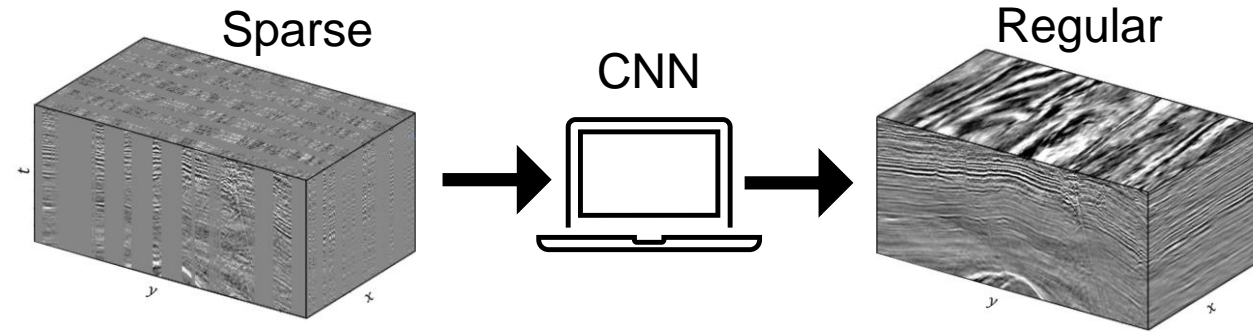


# Seismic processing

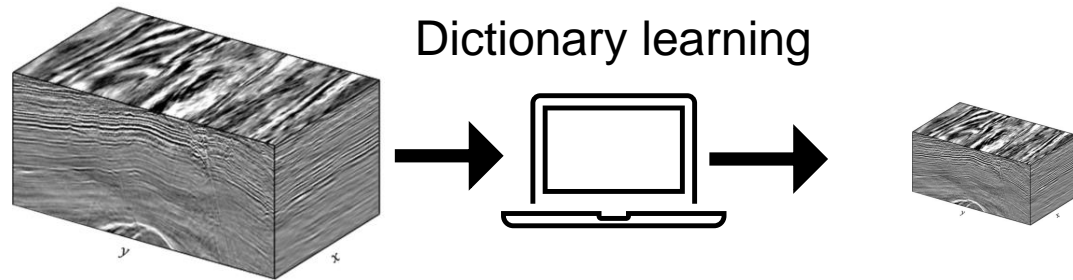
## Denoising



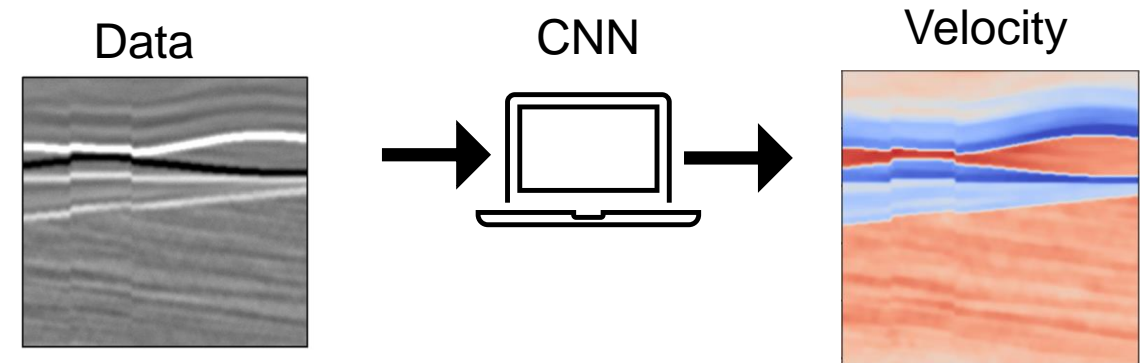
## Interpolation



## Data compression

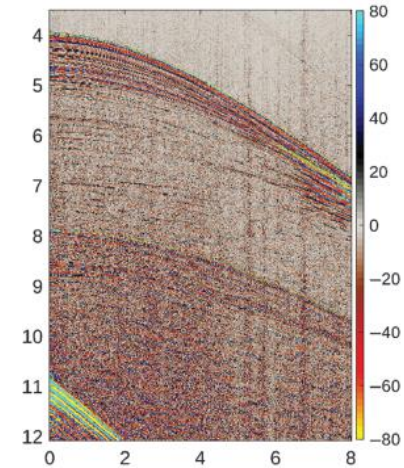


## Inversion / tomography

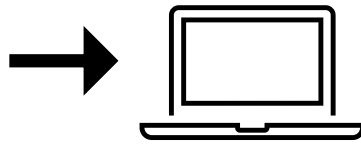


# Seismic data compression

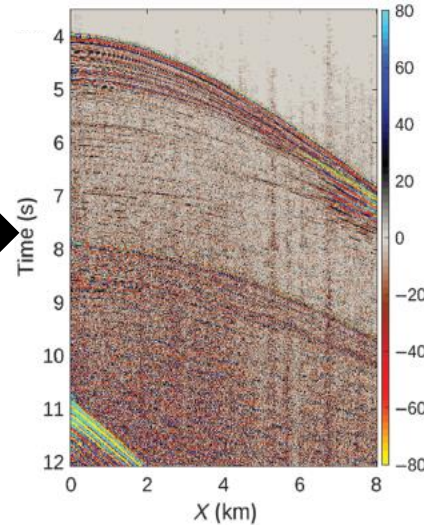
Raw data



Dictionary learning

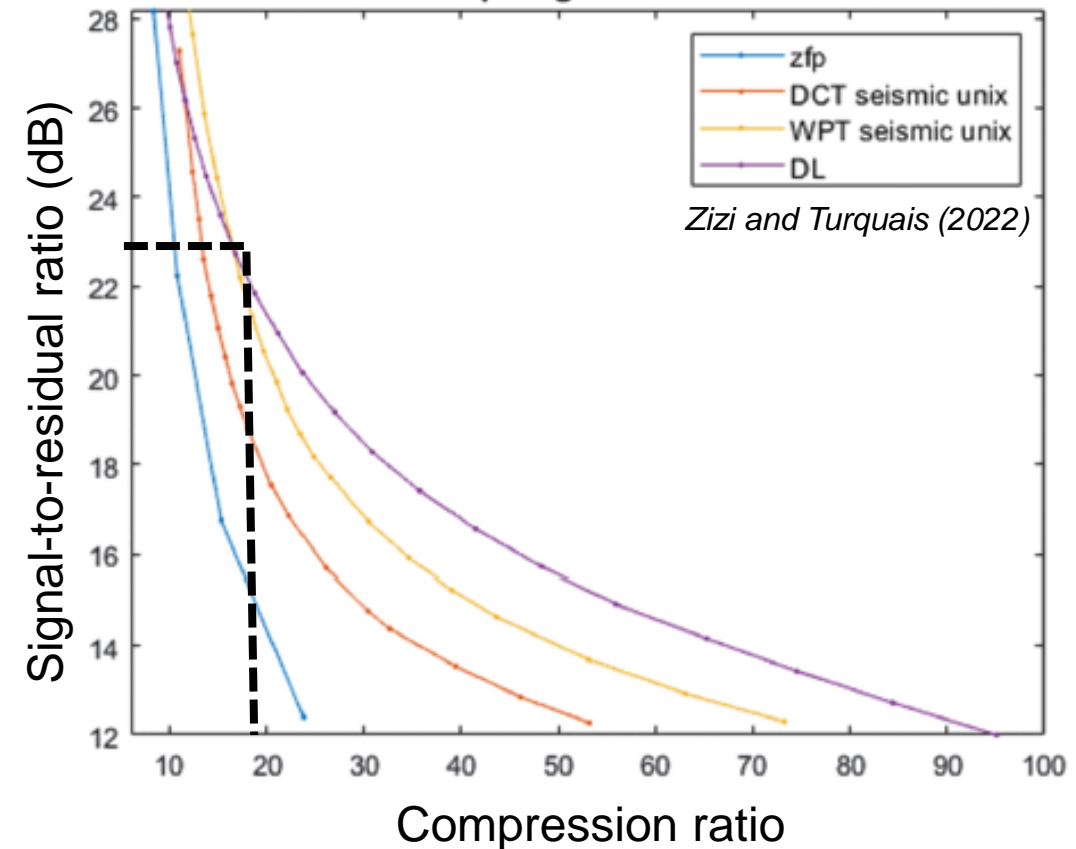


Data after  
compression/decompression



- **Deep learning-based** compression **outperforms** conventional techniques for **compression ratio** exceeding **20**
- Deep learning-based compression fully exploits the **redundancy** in the data and can significantly reduce **disk size requirements**

Performance of compression method





# Seismic data compression

Exact representation

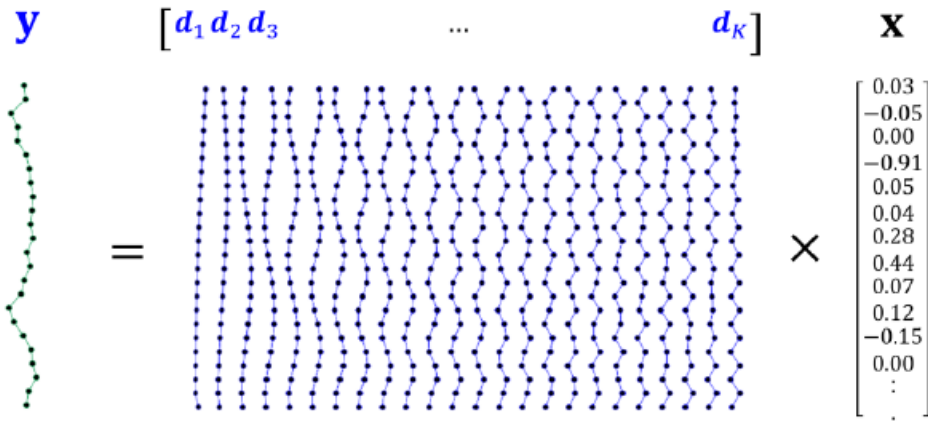
$$\mathbf{y} = [\mathbf{d}_1 \mathbf{d}_2 \mathbf{d}_3 \dots \mathbf{d}_K] \mathbf{x}$$


Diagram illustrating the exact representation of seismic data  $\mathbf{y}$  as a linear combination of basis vectors  $\mathbf{d}_1, \mathbf{d}_2, \mathbf{d}_3, \dots, \mathbf{d}_K$  weighted by coefficients  $\mathbf{x}$ . The basis vectors are shown as a grid of blue dots.

Sparse representation

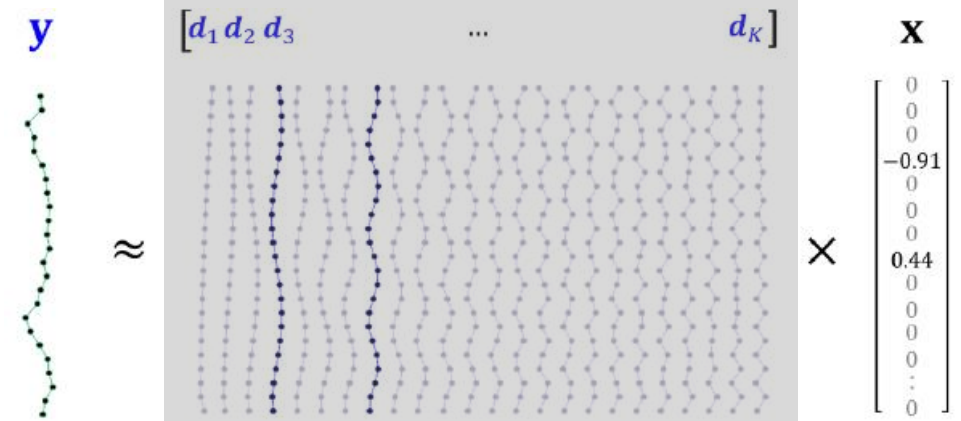
$$\mathbf{y} \approx [\mathbf{d}_1 \mathbf{d}_2 \mathbf{d}_3 \dots \mathbf{d}_K] \mathbf{x}$$


Diagram illustrating the sparse representation of seismic data  $\mathbf{y}$  as a linear combination of basis vectors  $\mathbf{d}_1, \mathbf{d}_2, \mathbf{d}_3, \dots, \mathbf{d}_K$  weighted by coefficients  $\mathbf{x}$ . The basis vectors are shown as a grid of blue dots, and the coefficients  $\mathbf{x}$  are shown as a vector with many zeros, indicating sparsity.

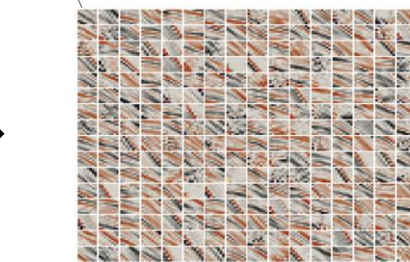
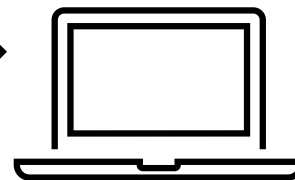
Zizi, PhD thesis (2023)

Dictionary learning



Shot gathers

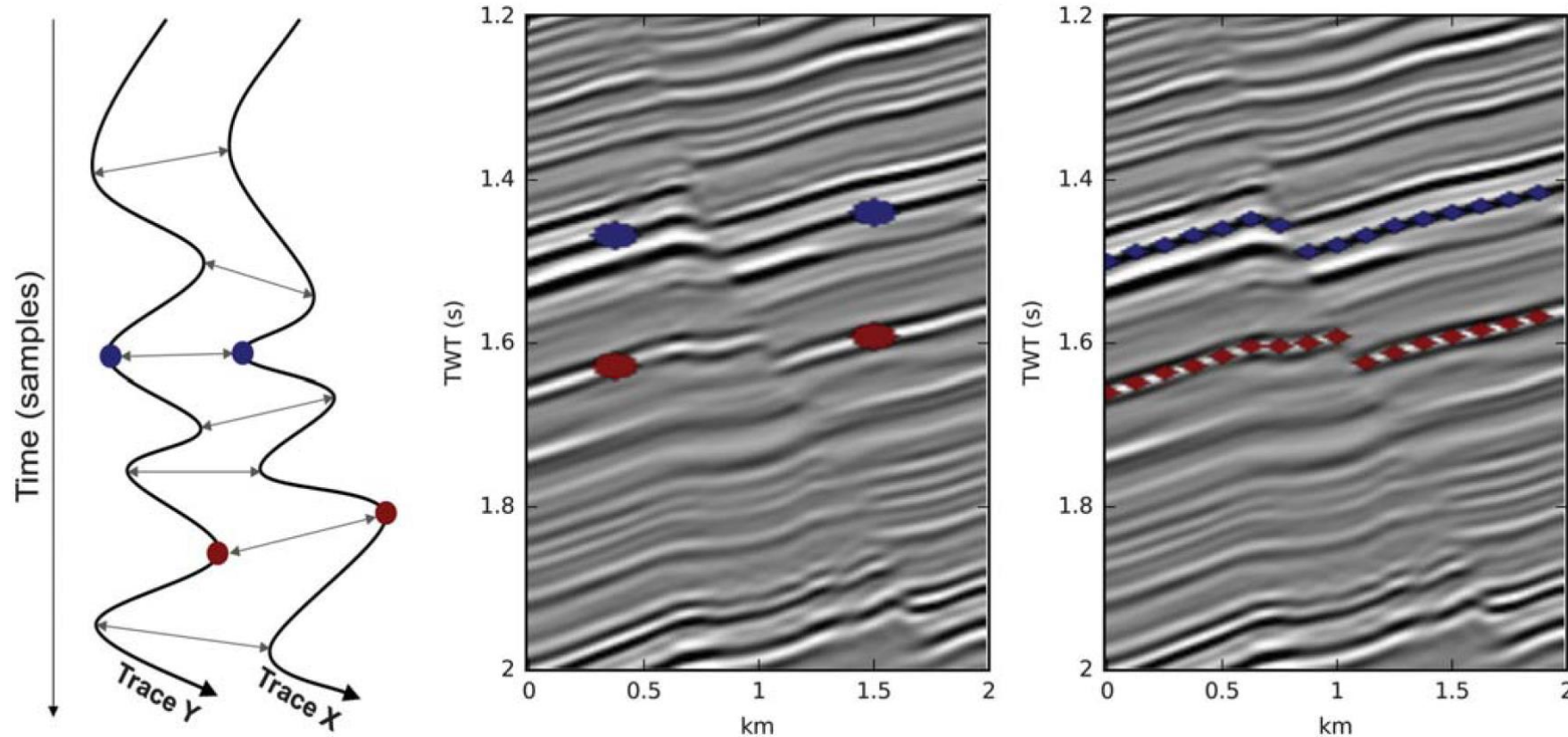
Singular Value Decomposition



Dictionary learned from data

Zizi and Turquais (2022)

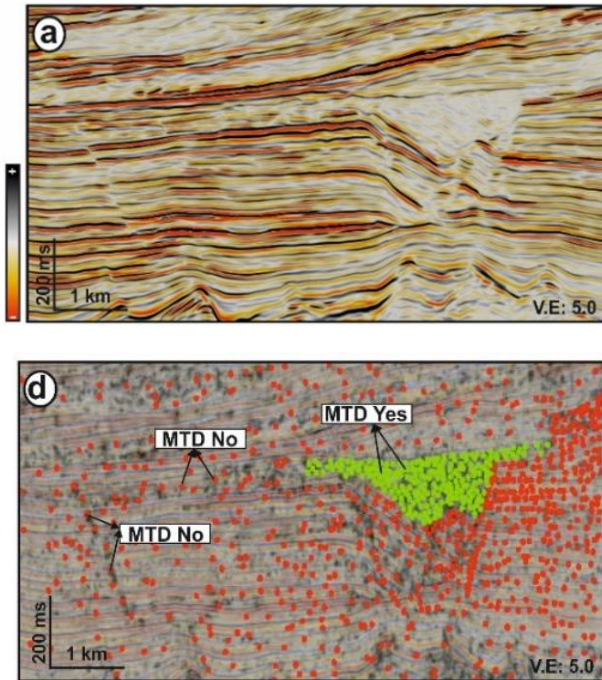
# Seismic interpretation



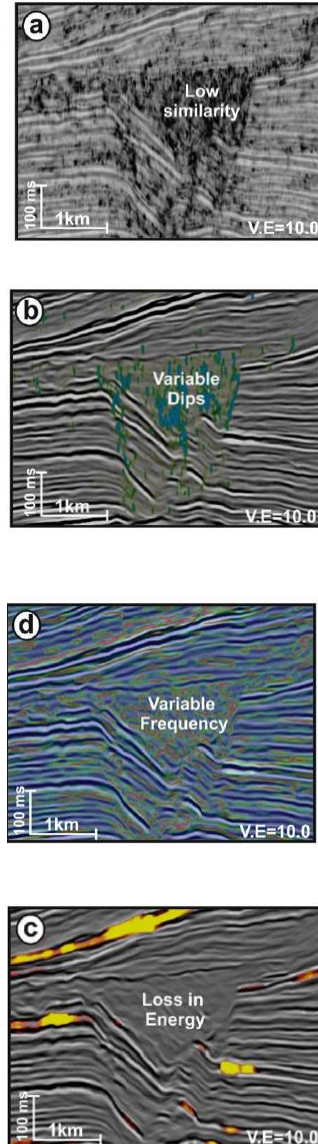
- **Dynamic time warping** measures the similarity between temporal sequences to find the optimal match. It is commonly used for speech recognition tasks.
- The algorithm can be used to track seismic horizons within a given sequences

# Automated interpretation of mass transport deposits

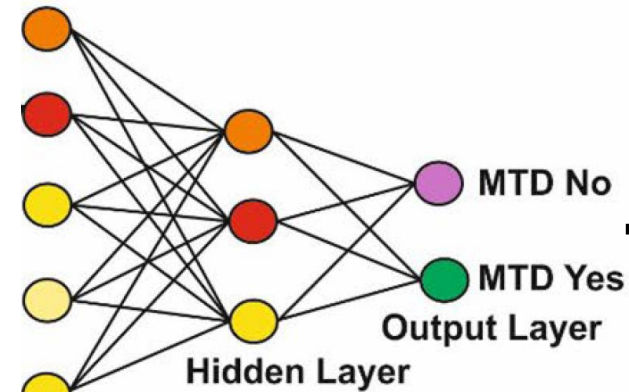
3D Seismic data  
~700 labels (MTD: yes/no)



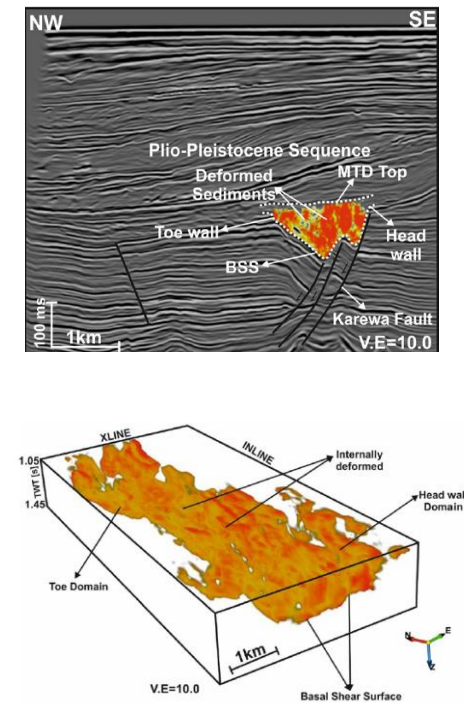
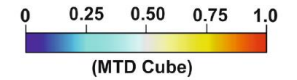
Seismic attributes



Feed-forward neural network  
(95% accuracy score)



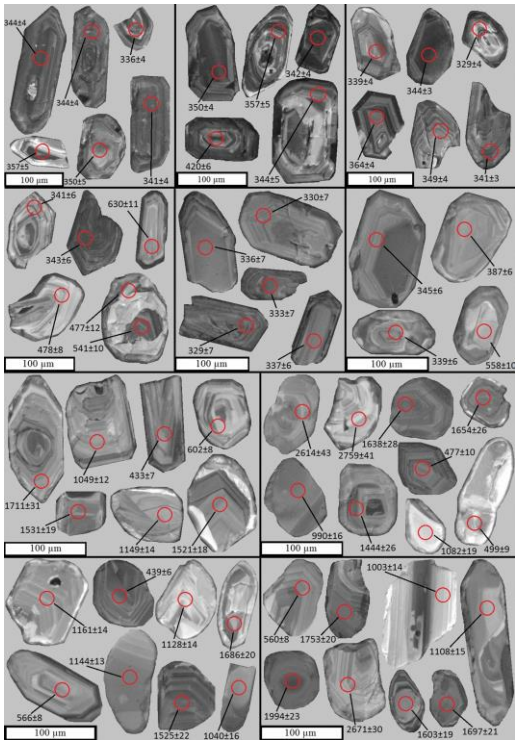
3D MTD geobody



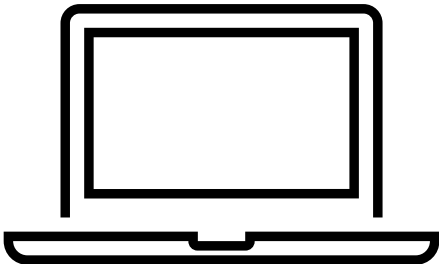


# Support Vector Machine

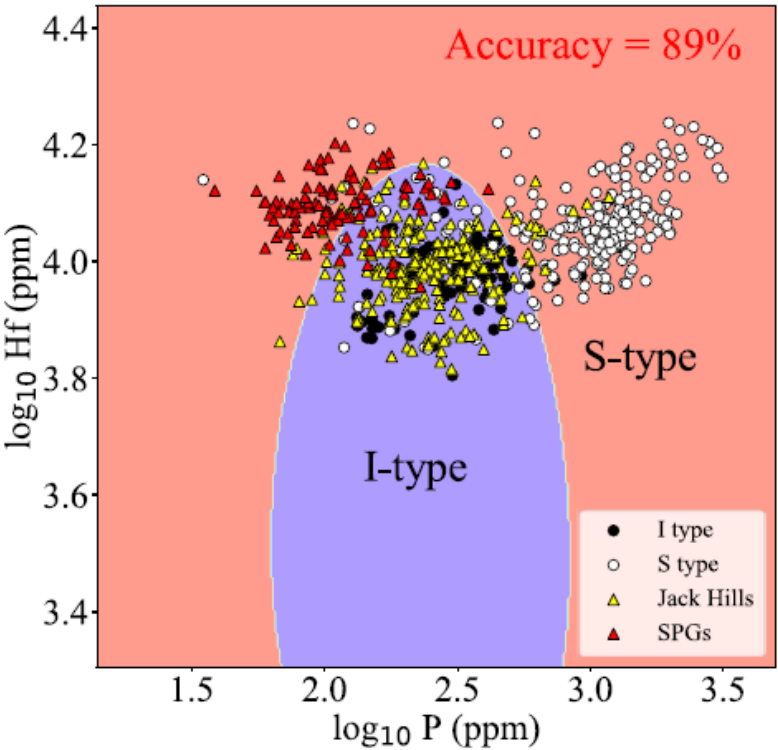
Zircon chemistry data



Support Vector Machine

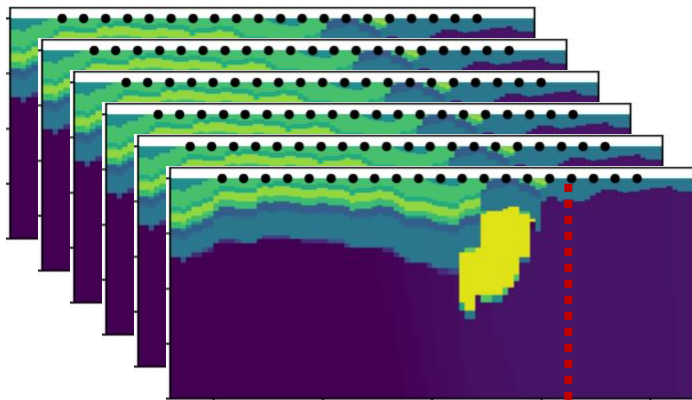


Classification task:  
Igneous (I-type) or Sedimentary (S-type) magma?



# Regression tree

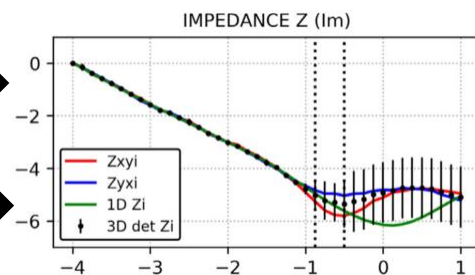
Synthetic Model



1D fwd

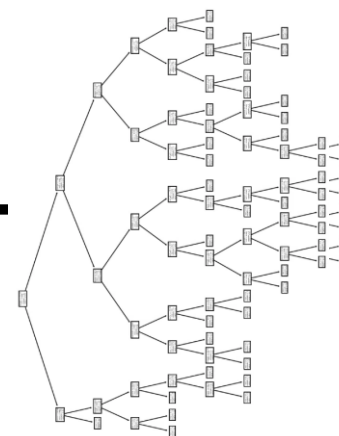
3D fwd

Synthetic MT Data



Dimensionality parameters

Regression tree

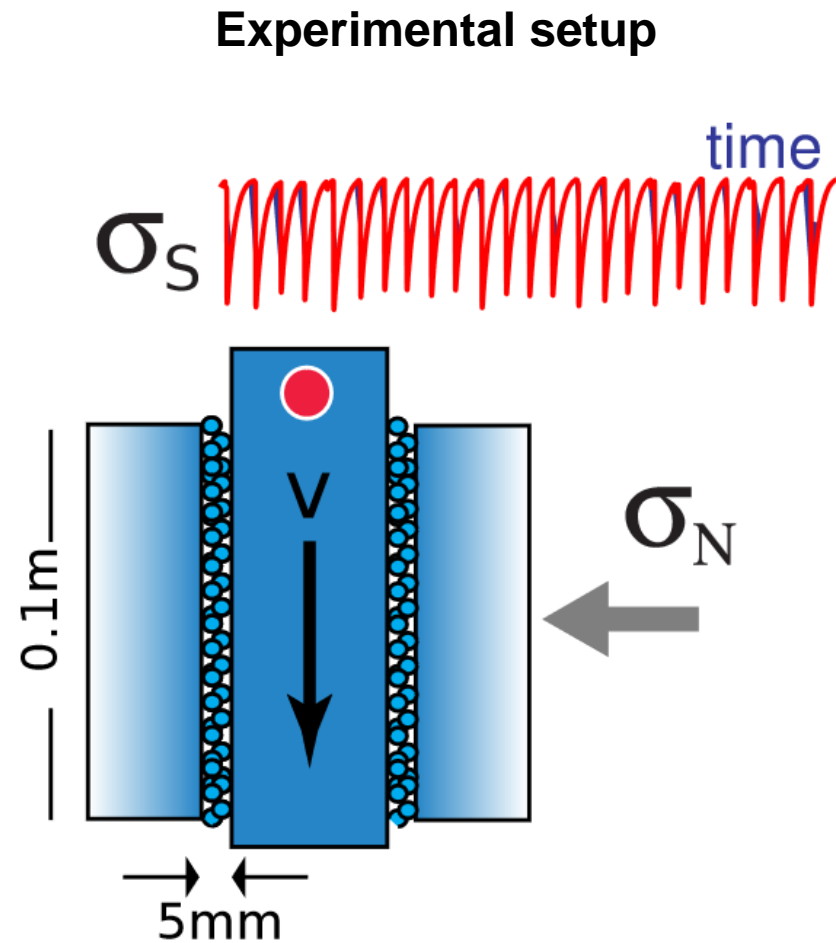
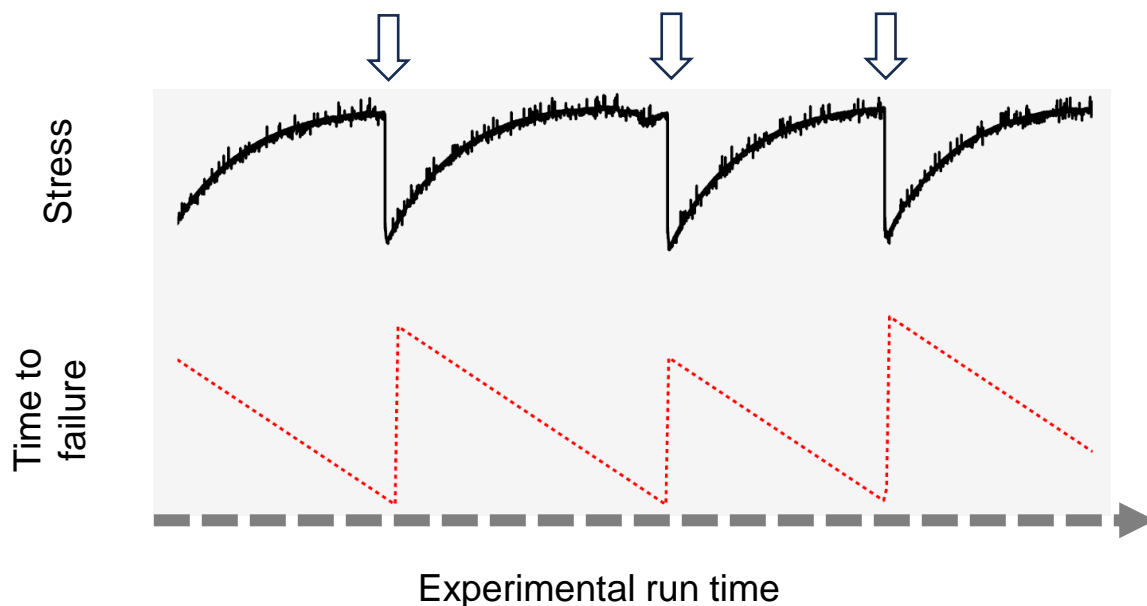


Dimensionality compensation error

- The objective of the workflow is to train a decision tree to **recognize 3D effects** in MT data and **compensate** for them in the data **uncertainty**
- This is a supervised ML algorithm that requires numerical modelling of the synthetic training set
- The resulting model performance and **generalization** depends the **accuracy** of the **numerical modelling** and the **volume** of data

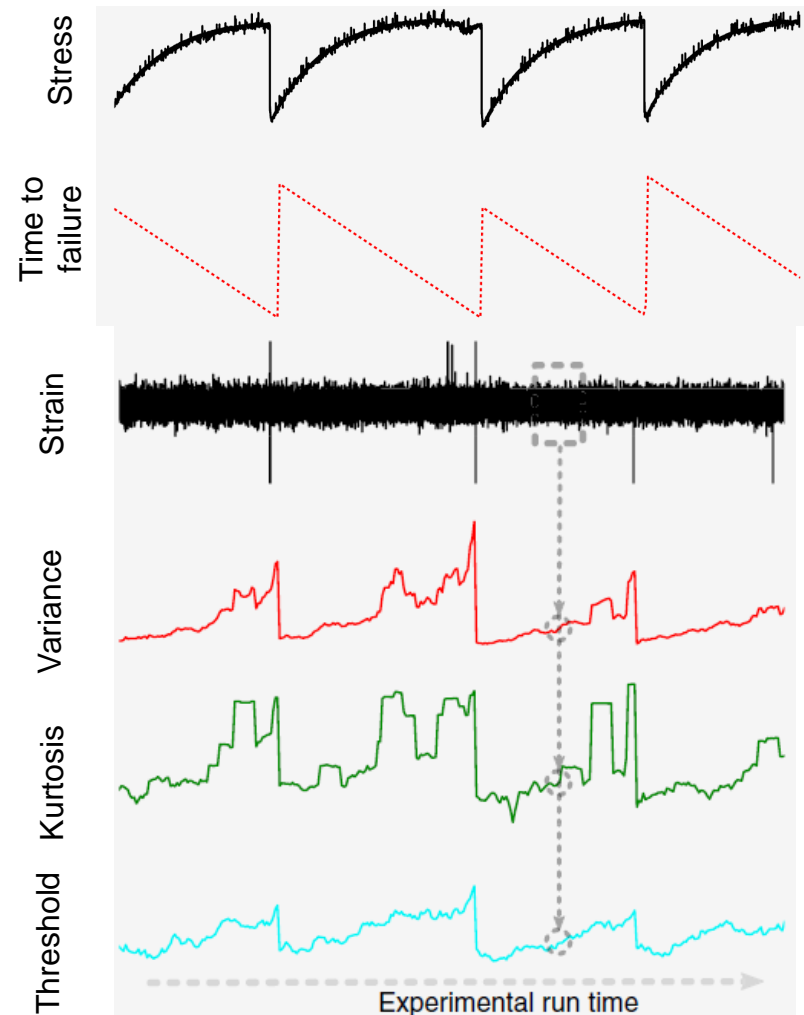
# Predicting laboratory earthquake with ML

- The objective of this study is train a ML model to predict the **time to fault failure** in a laboratory («Labquake»).
- The experiments is based on **continuous acoustic recording** with the goal to infer failure time
- Traditional approaches rely exclusively on **Earthquakes catalogs** that contain human biases

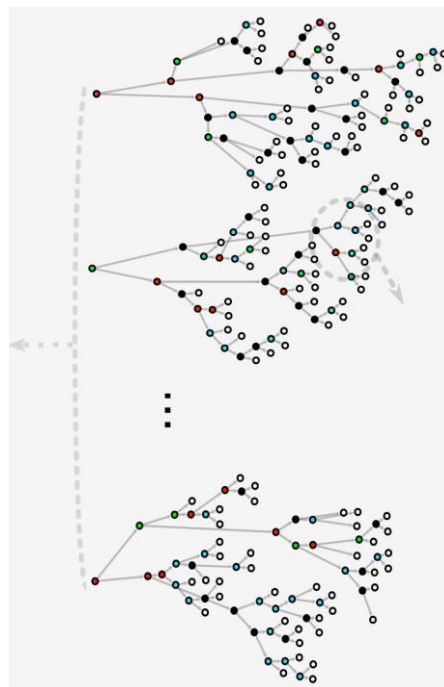


# Predicting laboratory earthquake with ML

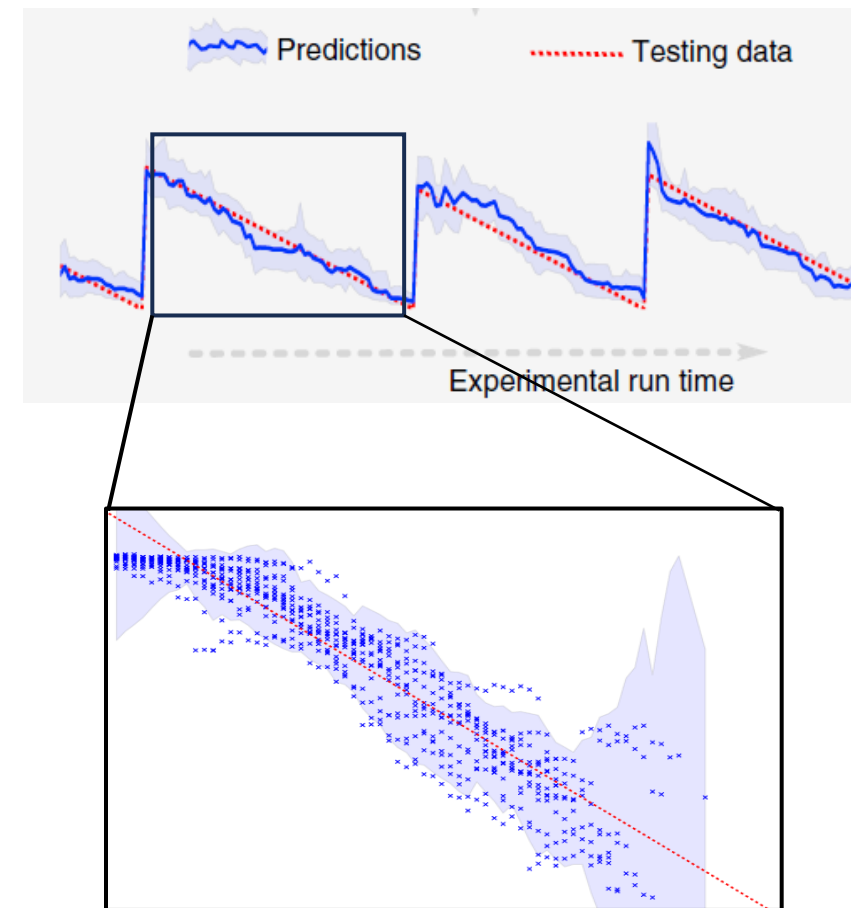
Data: Real-time acoustic recording



Random forest

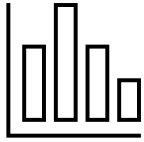


Prediction: Time to failure

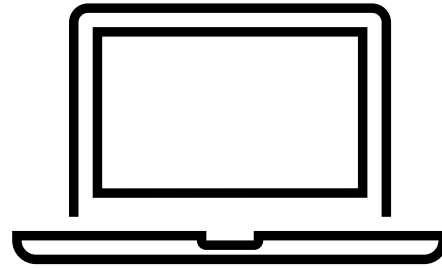


# Unsupervised learning - Clustering

Unlabeled Data

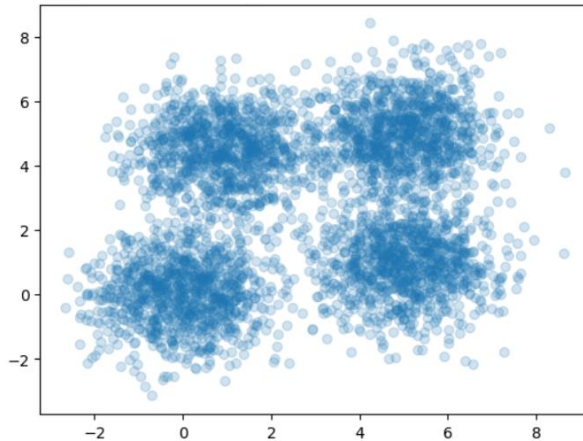


K-mean algorithm

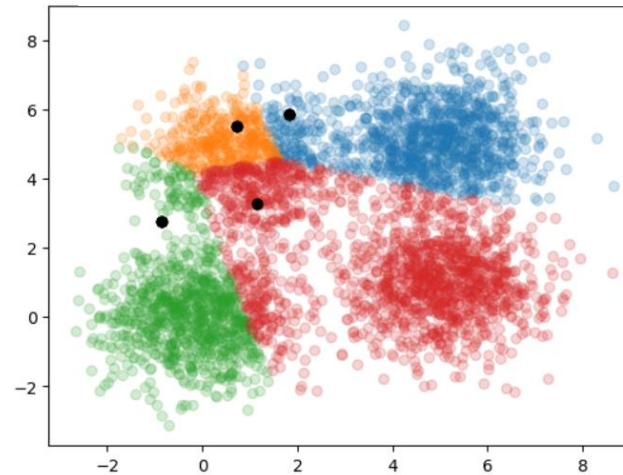


Clusters

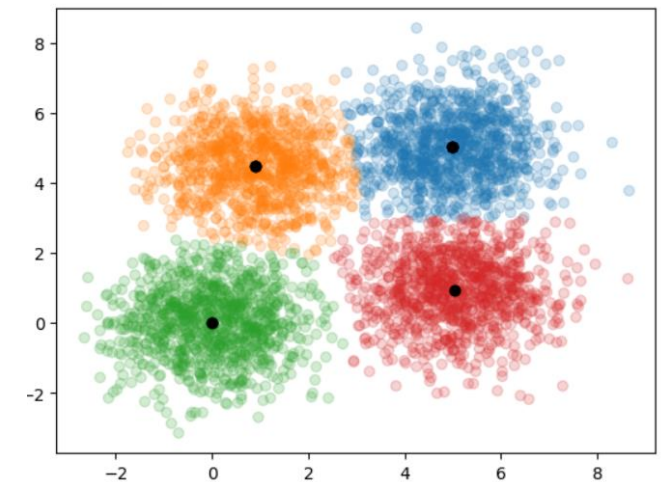
Unlabeled dataset



Random initialization

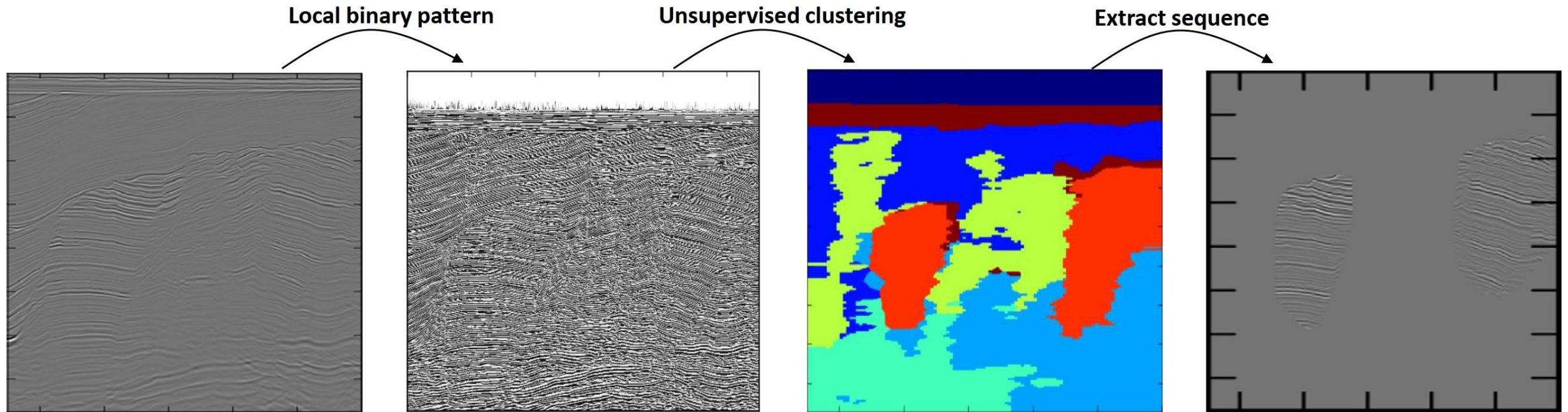


Final clusters



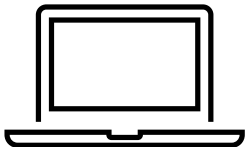
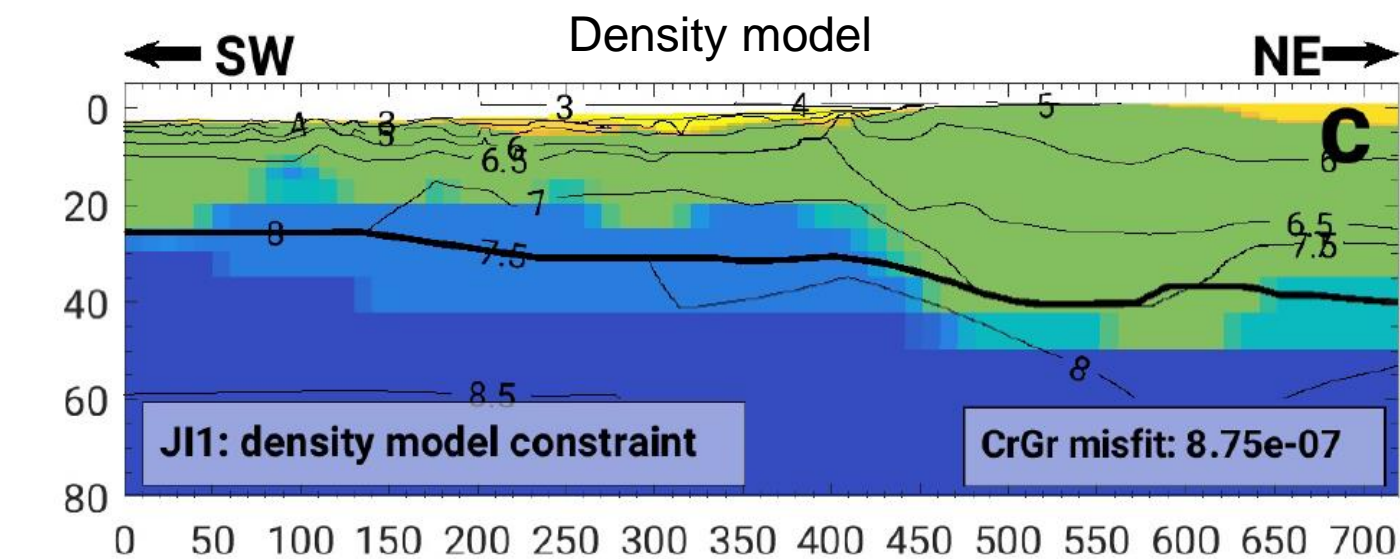
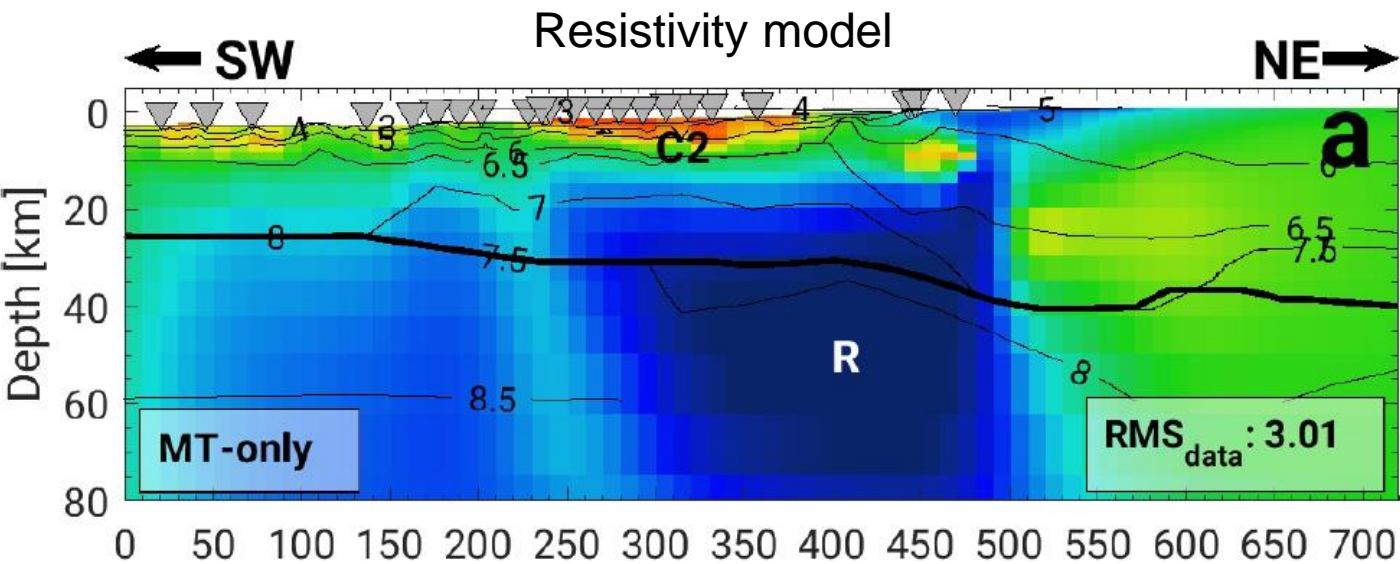


# Clustering

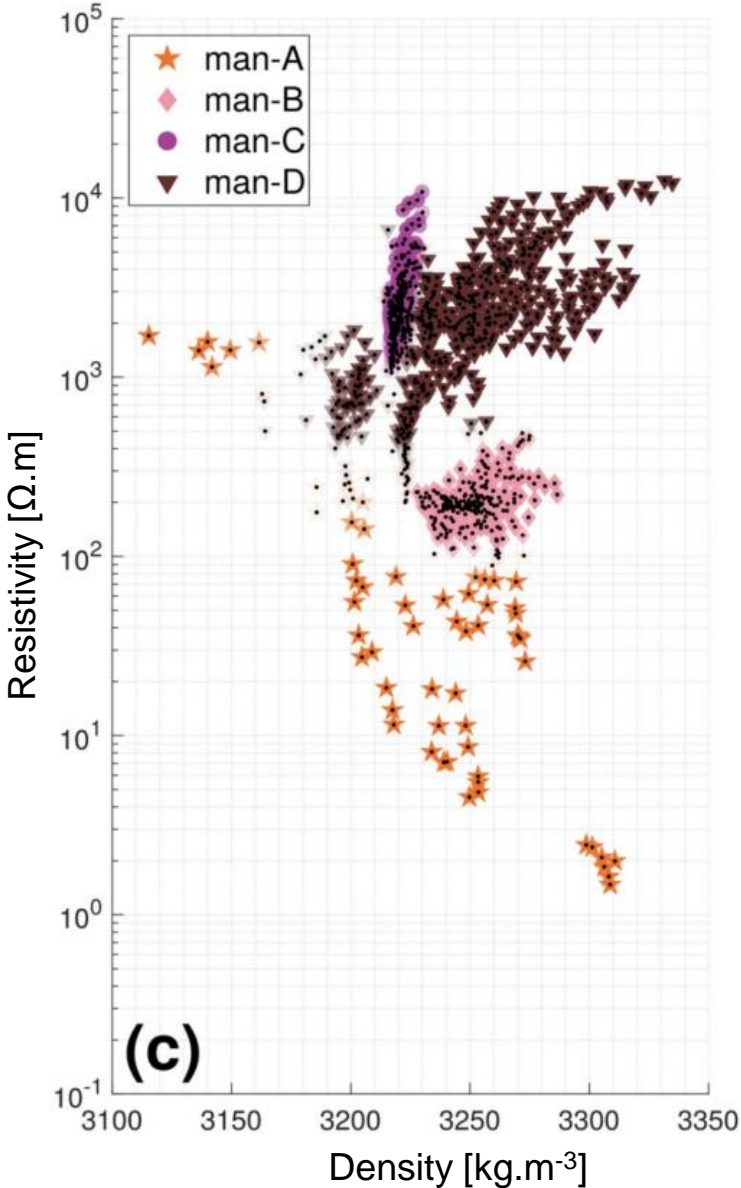


- **Clustering** is an **unsupervised** ML method. The task is to group data-set into **distinct categories** based on some measure of equality of the data. This measure is often referred to as a **metric** or **(dis)-similarity measure**. The **K-mean clustering** algorithm uses the euclidian distance as metrics.

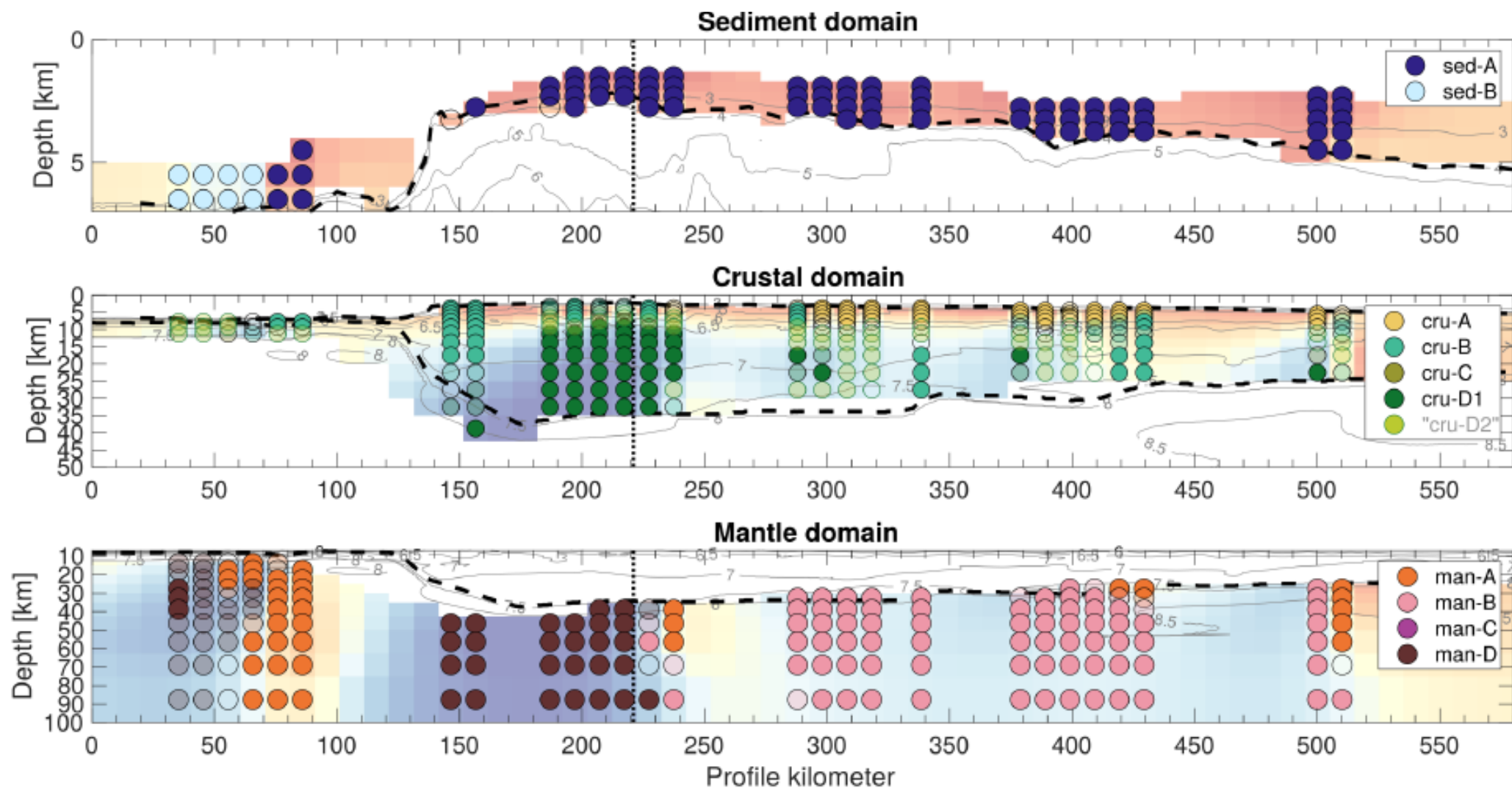
# Clustering



Clusters in mantle domain



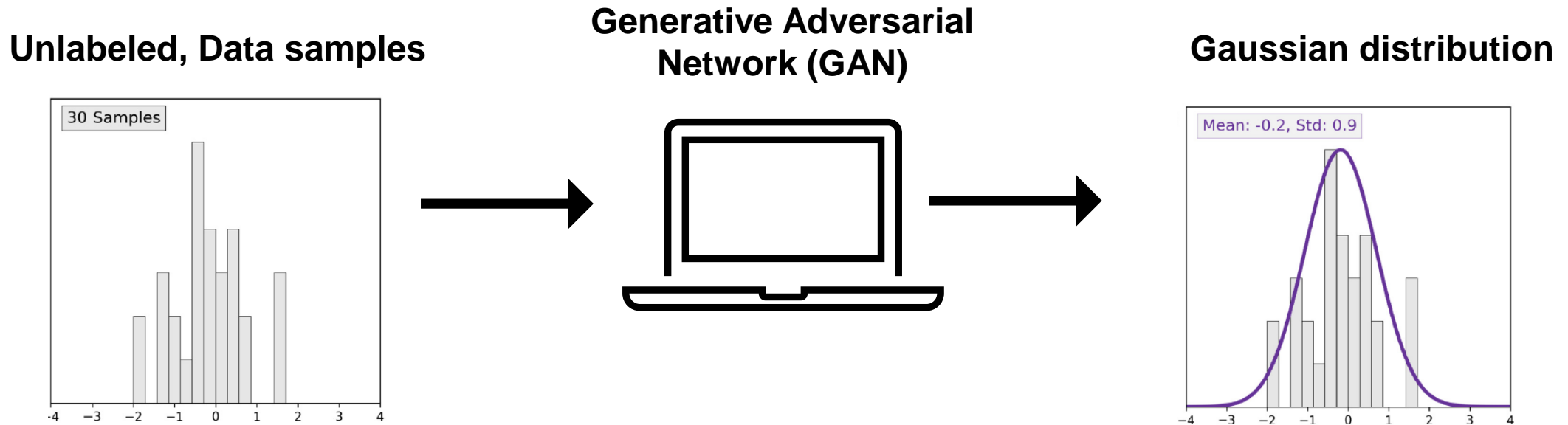
# Clustering



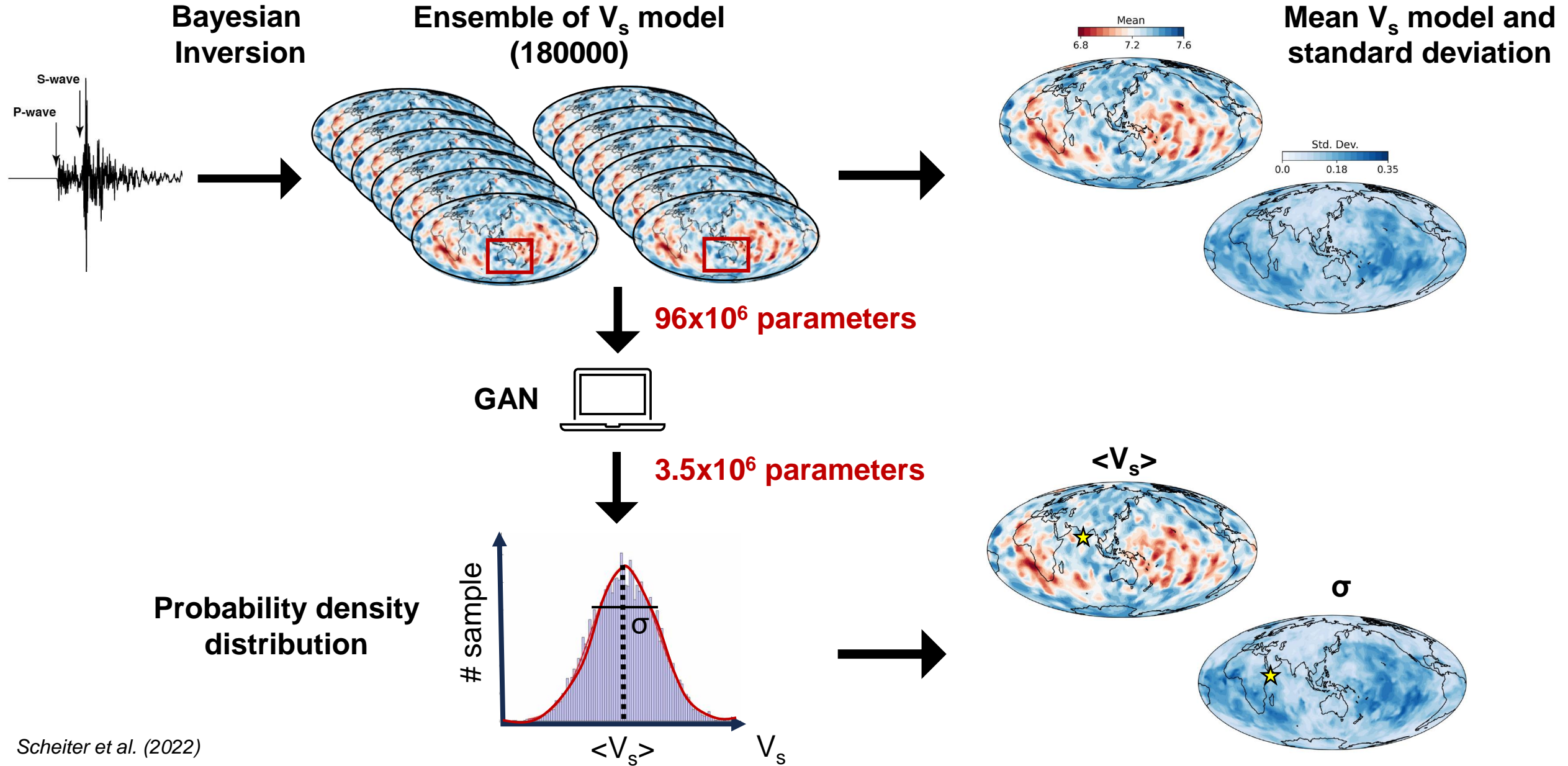


# Generative models

- **Generative modeling** is a branch of machine learning that involves training a model to produce **new data** that is **similar** to a given dataset.
- The generative modeling learns a **probability distribution** from training samples
- The objective is to build a model that can generate **new sets of features** that look as if they have been created using the same rules as the **original data**



## Shear velocity at mantle-core boundary



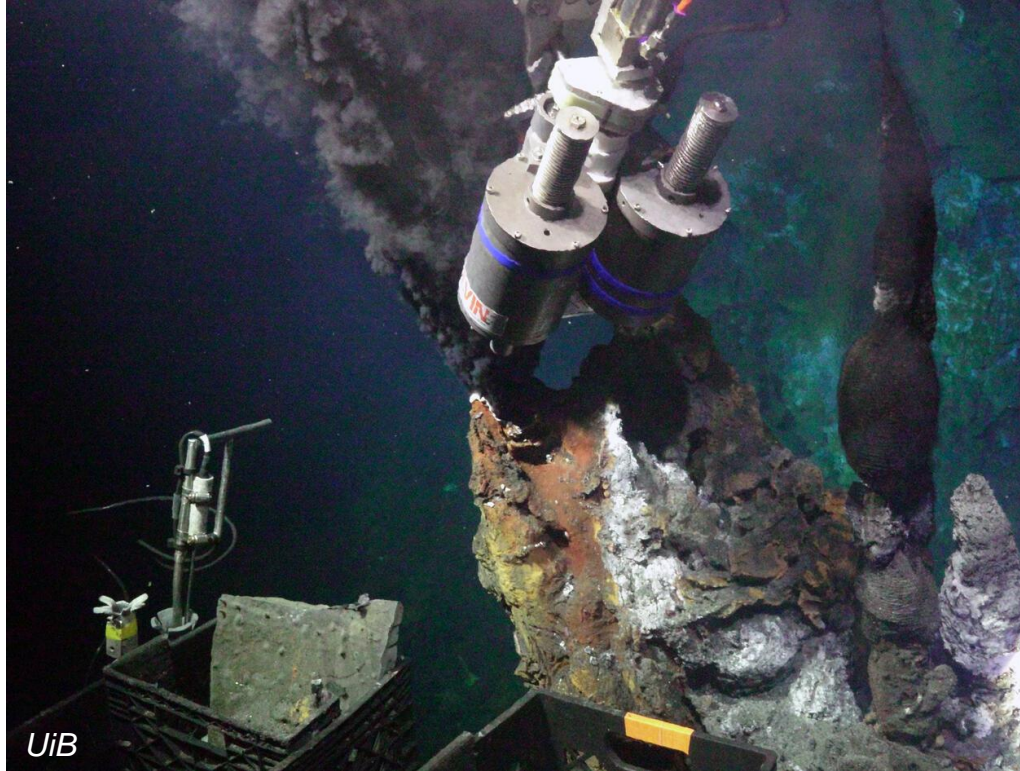


# **Perspectives for AI in geophysics**



# Data acquisition – autonomous vehicles

Deep sea exploration



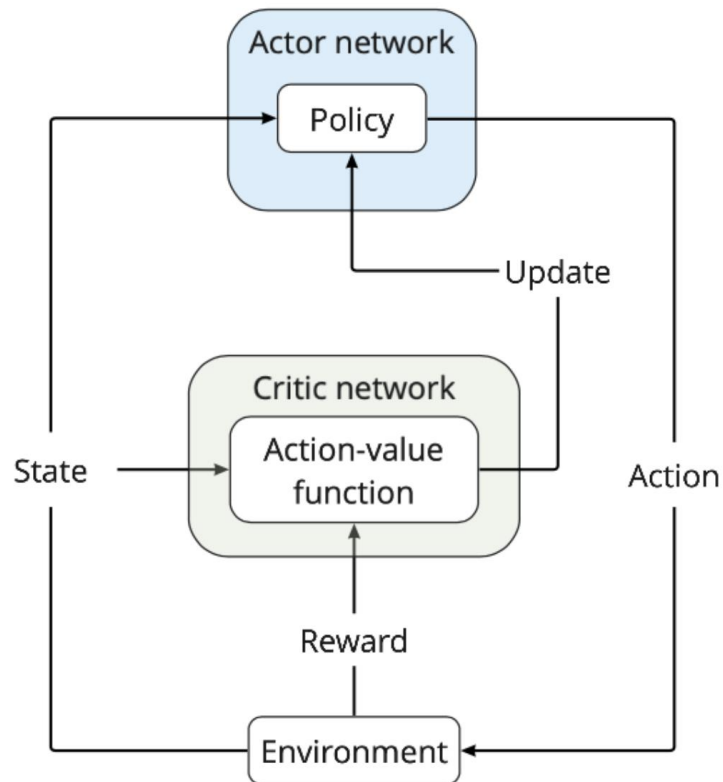
Autonomous underwater vehicles (AUVs)



- Access to challenging and remote environments requires advanced autonomous technologies
- How can an AUV on a mid-ocean ridge at 3000 meters under the surface automatically correct for its sail lane?

# Deep Reinforcement learning

- **Reinforcement Learning** is inspired by behavioural psychology, where learning is achieved by **trial-and-error**, solely from **rewards** and punishments, interacting with a dynamic **environment**
- Deep reinforcement learning use neural network ability to learn from **pixels** or creating control policies in robotics based on sensors like **camera inputs**

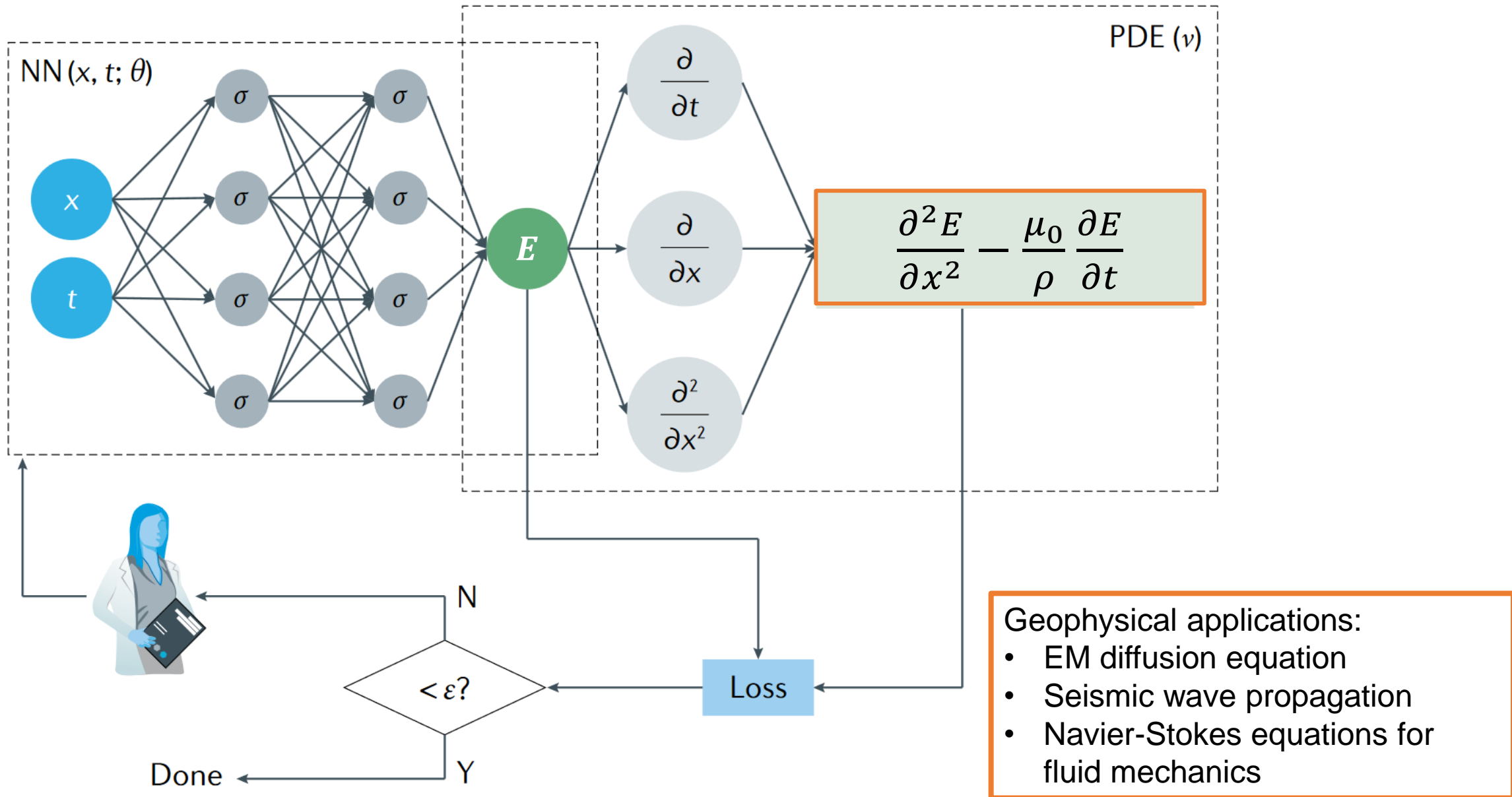


## Example

- Actor/Agent: Robot, AUV
- Environment: Deep sea, mid-ocean ridge
- State: Position, sail line etc.
- Policy: Correct sail line to avoid collision
- Action: Correct sail line by 15 degrees

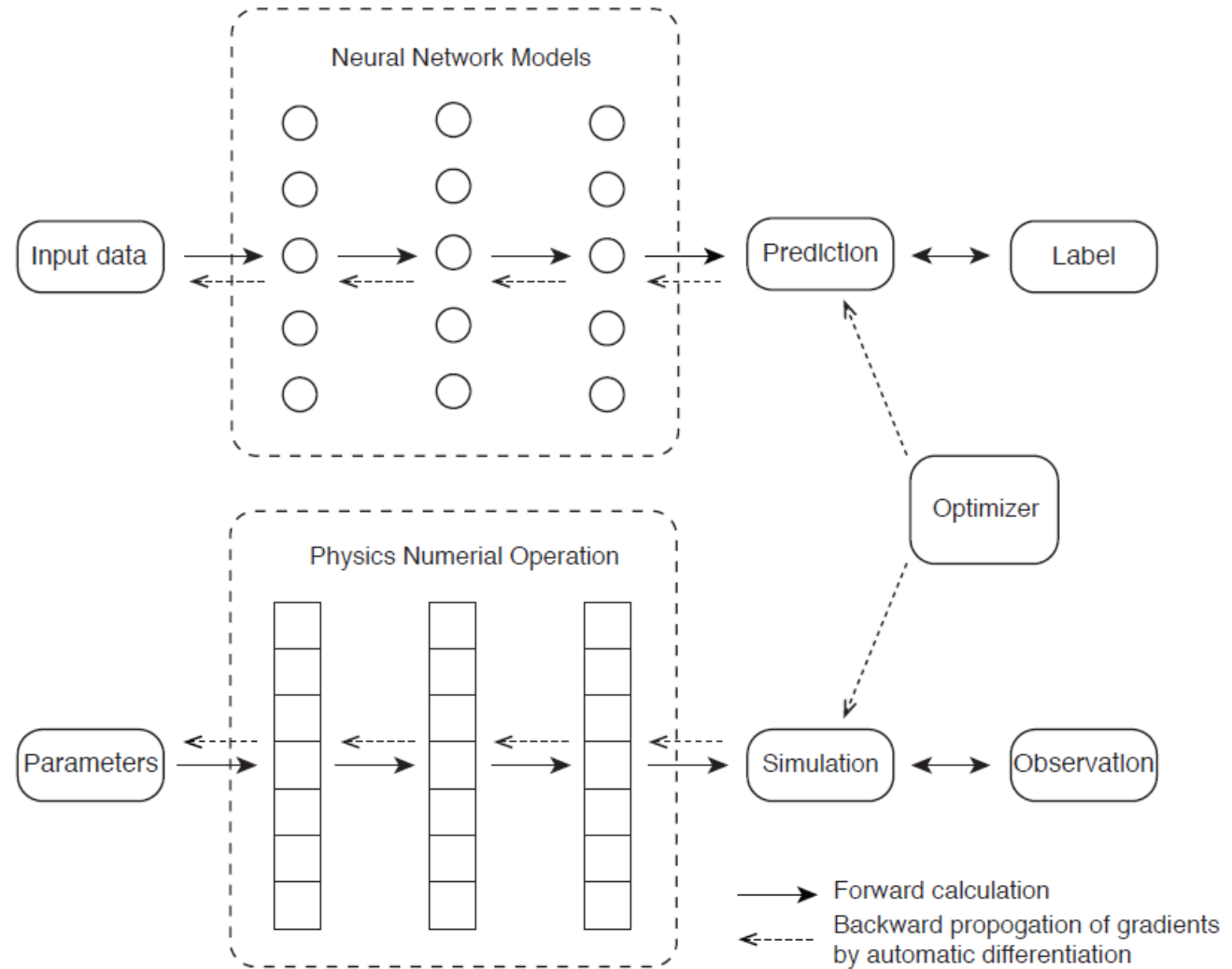


# Physics-informed neural network (PINN)



# PINN for inverse problem

- PINN can **outperform grid-based**, traditional, ill-posed inverse problem
- PINN, also known as hybrid modelling, will obey physical laws while being fully **adaptative** when **theory is weak**
- PINN will not replace physical modelling but **complement** it and **enrich** it
- PINN for inverse problem is build on deep learning **framework** (TensorFlow, PyTorch) and do not require **expensive softwares**!

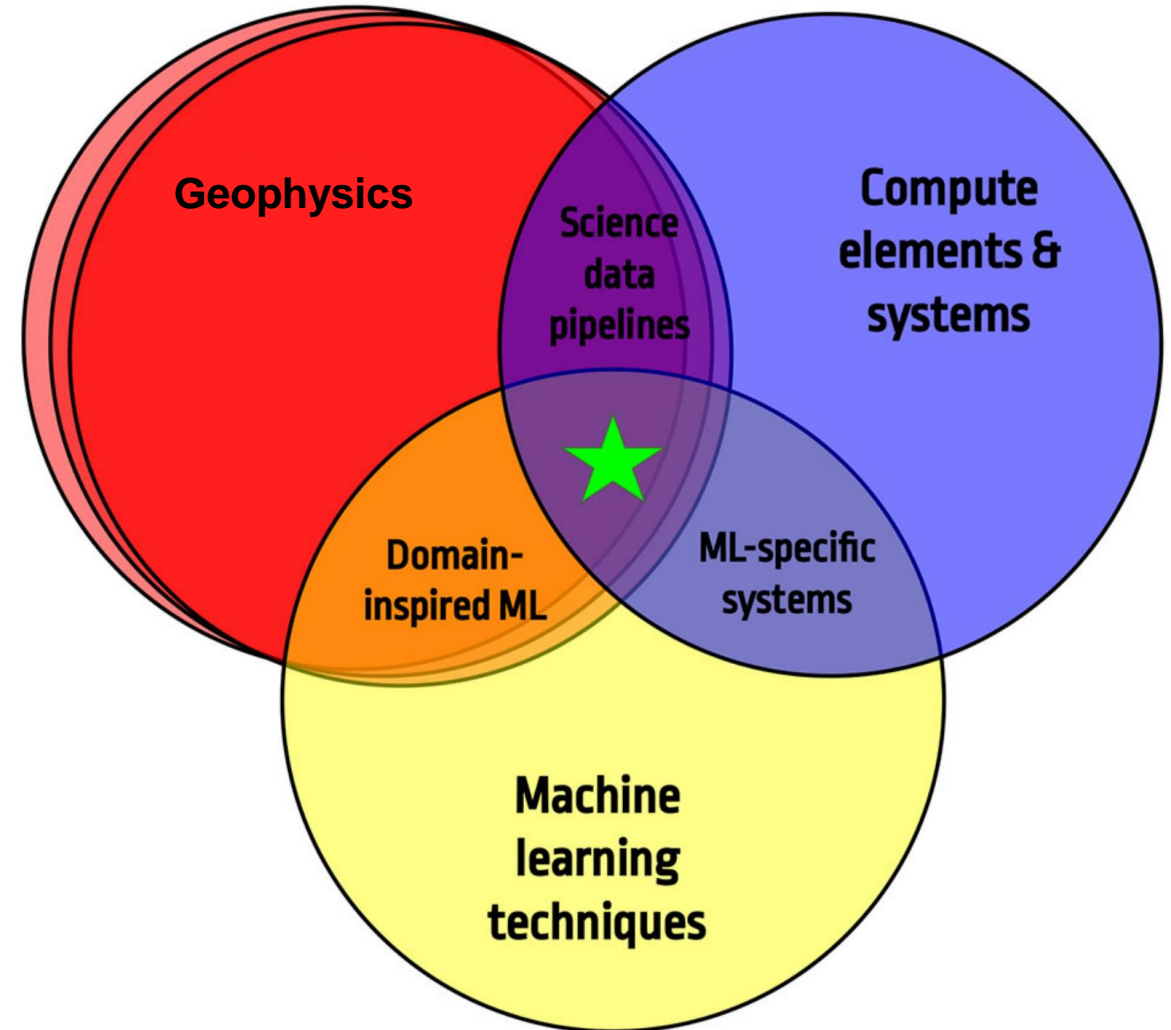


# Fast Machine Learning

“The more efficiently we can test hypothesis, the faster we can achieve discovery”

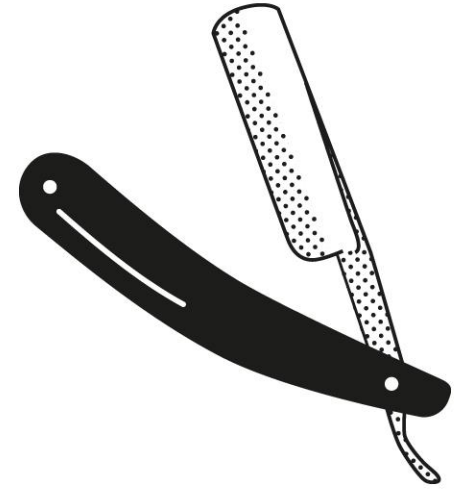
Deiana et al. (2022)

- The concept of fast ML is to find the confluence of domain-specific challenges, ML and High-Performance computing to accelerate Science.



# Breaking the curse of non-uniqueness?

- For the inverse problem, PINN can substitute grid-based modelling at a lower computational cost
- PINN can be adapted to Bayesian inversion schemes to produce large ensemble of models
- Train generative models from samples to optimize storage size
- We can expect dramatic improvement in the characterization of the solution space and uncertainty quantification.



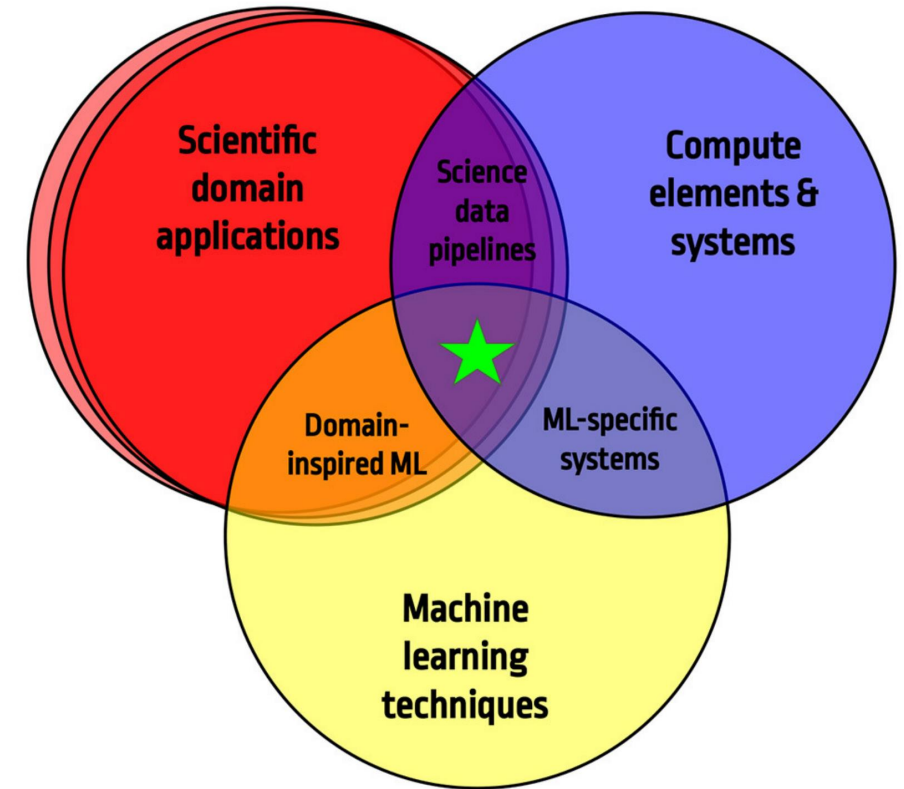
*The end of Occam's razor?*



# **Conclusions**

# Conclusions

- Machine Learning for **Geophysics**: benefits from advances in **high-performance computing**
- Let's remind us that machine learning has an **environmental impact**.
- Nowadays, AI is pretty much about Machine Learning, which is in turn linked to advances in the field of **deep learning**
- Will **machine learning** break the **curse of non-uniqueness** in geophysical inversion?
- In an **educational** perspective, there is a need for a **demystification** of AI
- Train and provide **guidelines** to students, understand the **limitations** and **ethical** implications of AI (data privacy, accountability etc.)



The background features a complex, abstract network of glowing orange and yellow lines and nodes, resembling a neural network or a web of connections. The lines are thin and wavy, while the nodes are larger, rounded, and emit a bright glow. The overall color palette is warm, with shades of orange, yellow, and light pink.

**Thank you for your attention!**