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Modern Machine Learning and its Application to Geospatial Data

Jonathon Hare, 6/9/2024

What is machine learning?

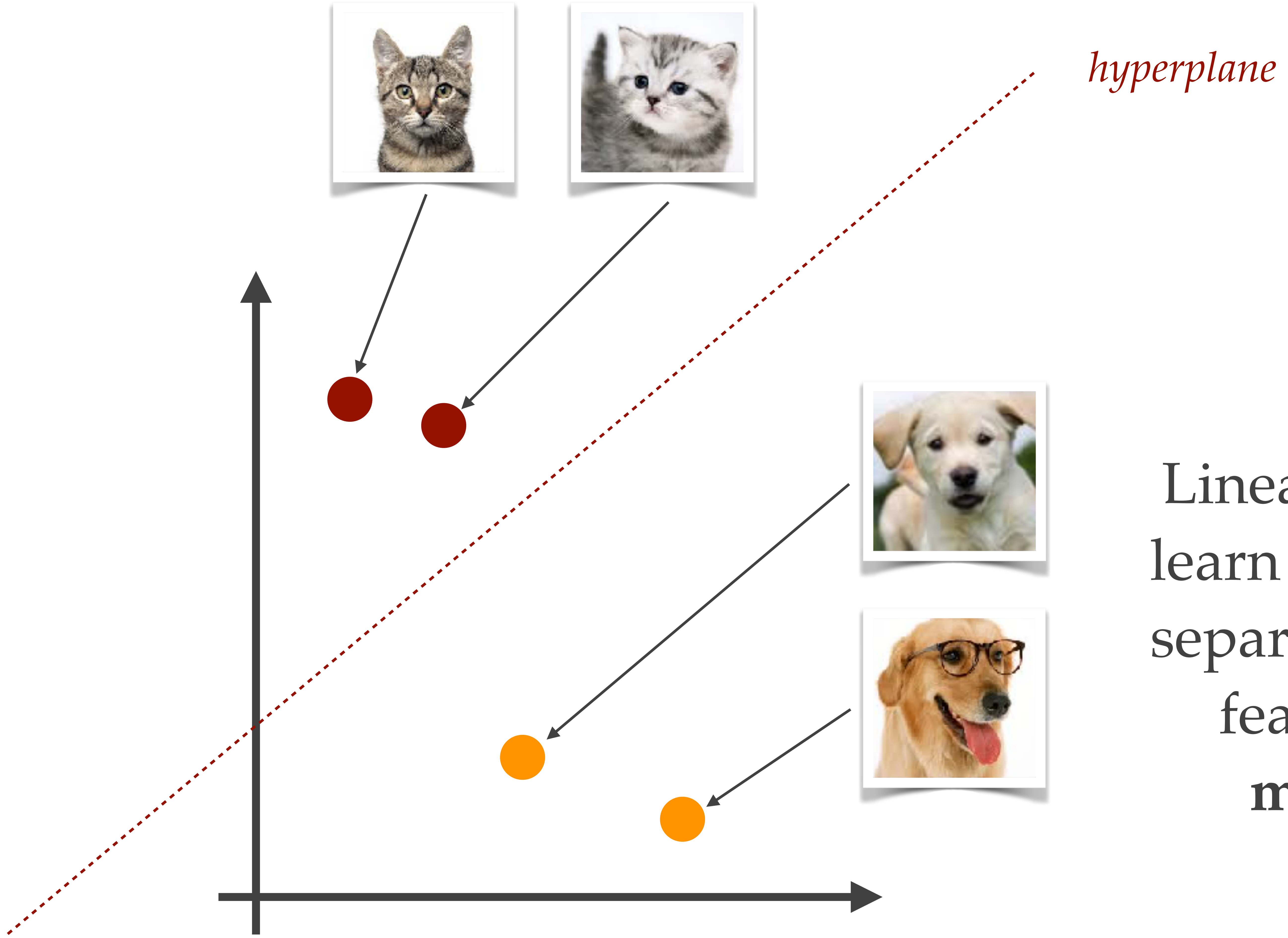
Supervised learning

Classification

- Classification is the process of assigning a **class label** to an **input**.
- A supervised machine-learning algorithm uses a set of pre-labelled training data to learn how to assign class labels to vectors (and the corresponding objects).
- A binary classifier only has two classes
- A multiclass classifier has many classes....

Supervised learning

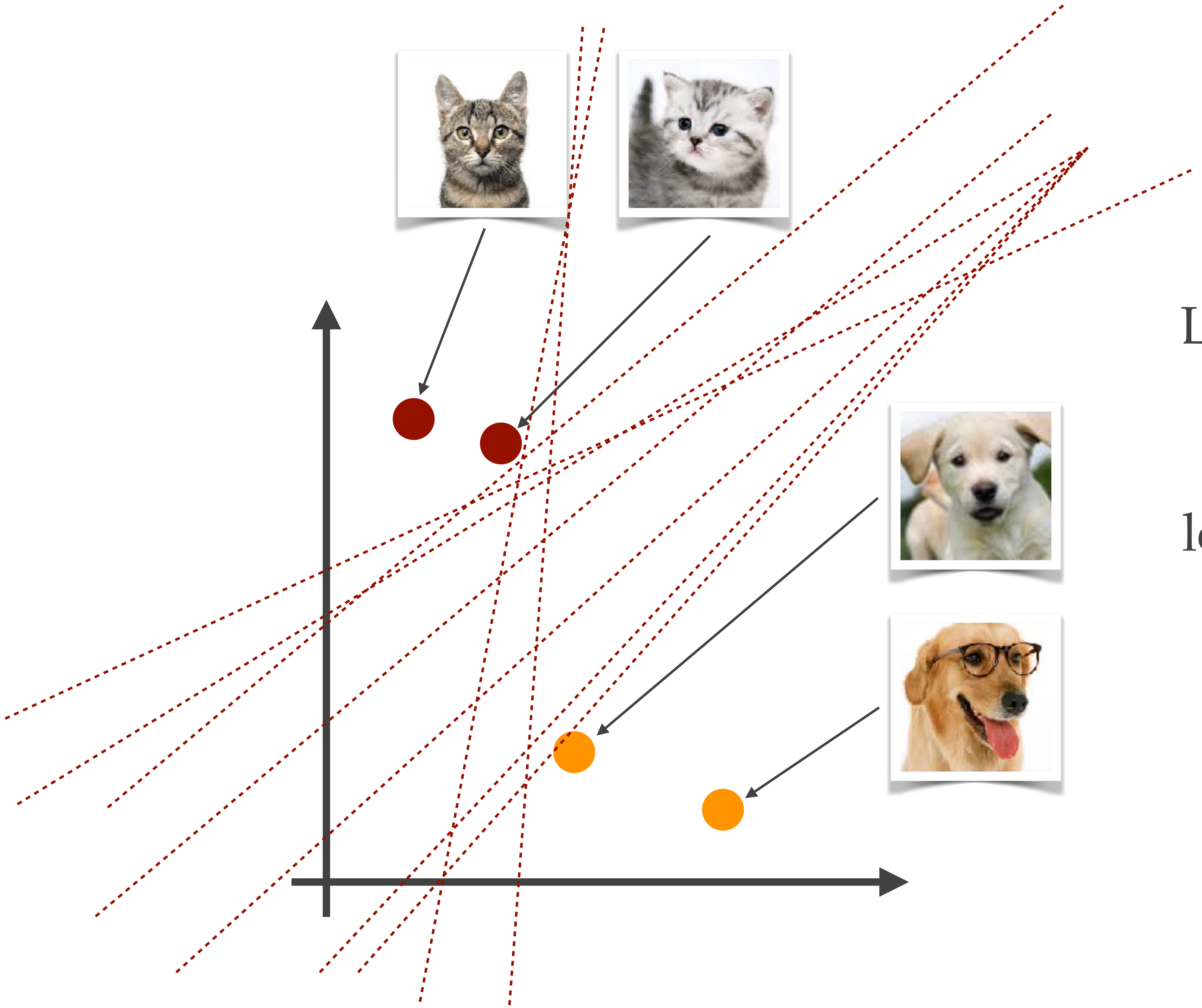
Linear Classifiers



Linear classifiers try to learn a **hyperplane** that separates two classes in feature space with **minimum error**

Supervised learning

Linear Classifiers



Lots of hyperplanes to choose from… different machine learning algorithms find different solutions

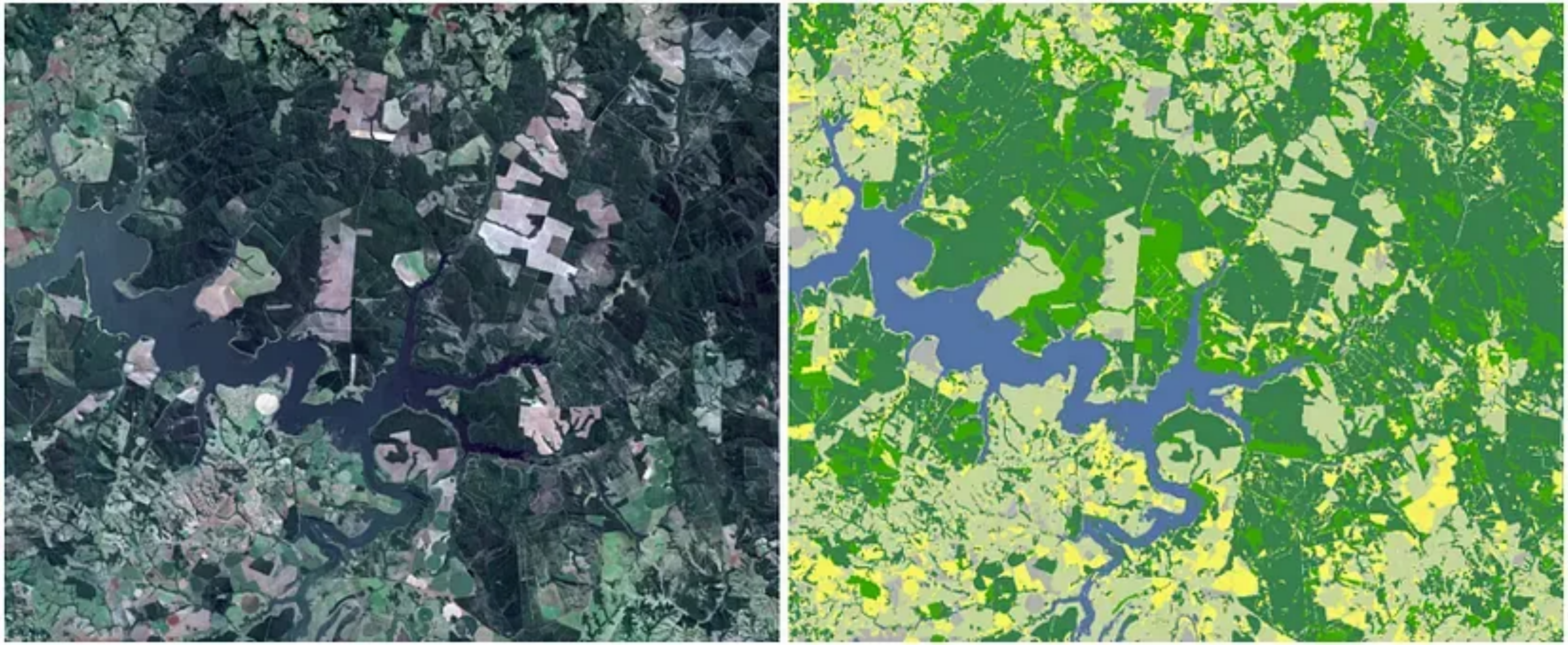
Supervised learning

Classification

- Demo…

Supervised learning

E.g. Land Use Classification



Objective: predict a class for every location in the input image

Image from https://medium.com/@limeira.felipe94/machine-learning-and-deep-learning-for-land-use-classification-using-arcgis-pro-9d304130a51e

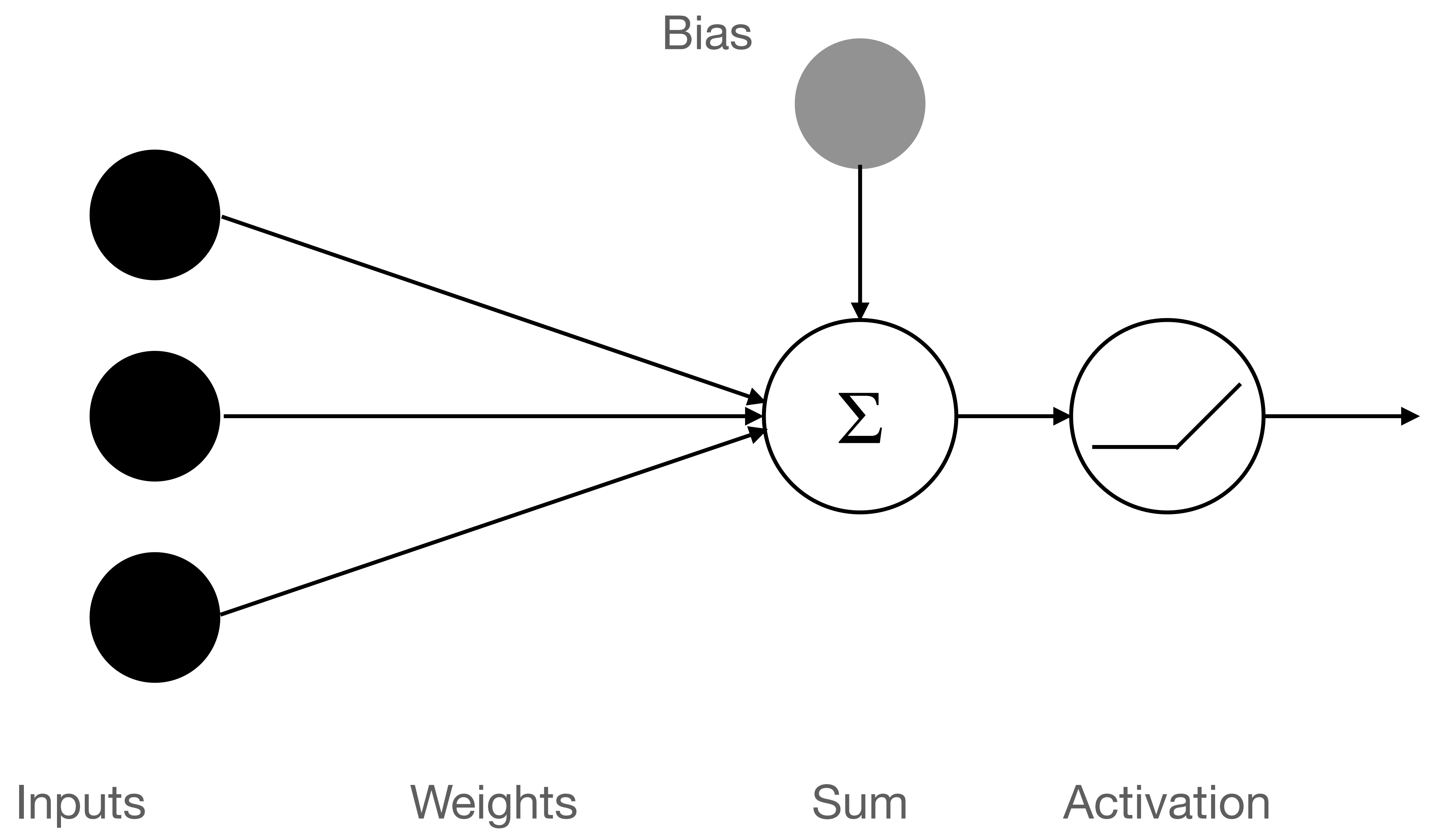
How does it work?

Representing data as numbers

How does it work?

Modern machine learning with neural networks

- Almost all modern machine learning is based around a simple idea of an artificial neuron



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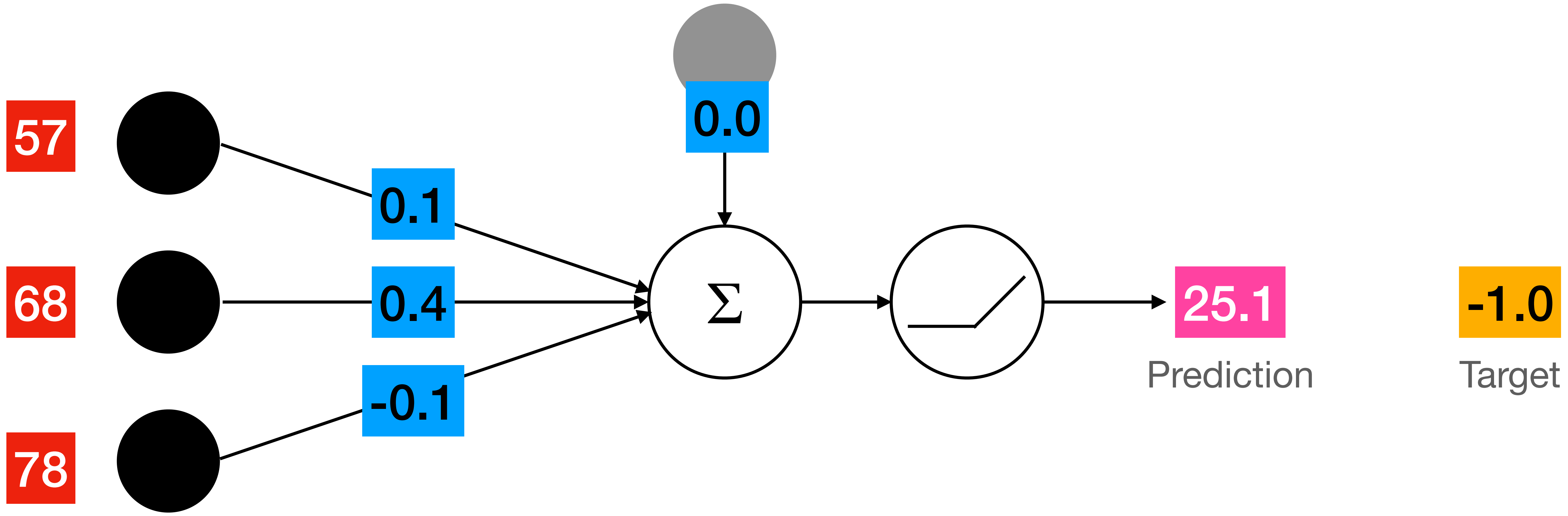

Learning is the process of adjusting the weights & bias so that the prediction is close to the target ***for all training examples***

How does it work?

Modern machine learning with neural networks

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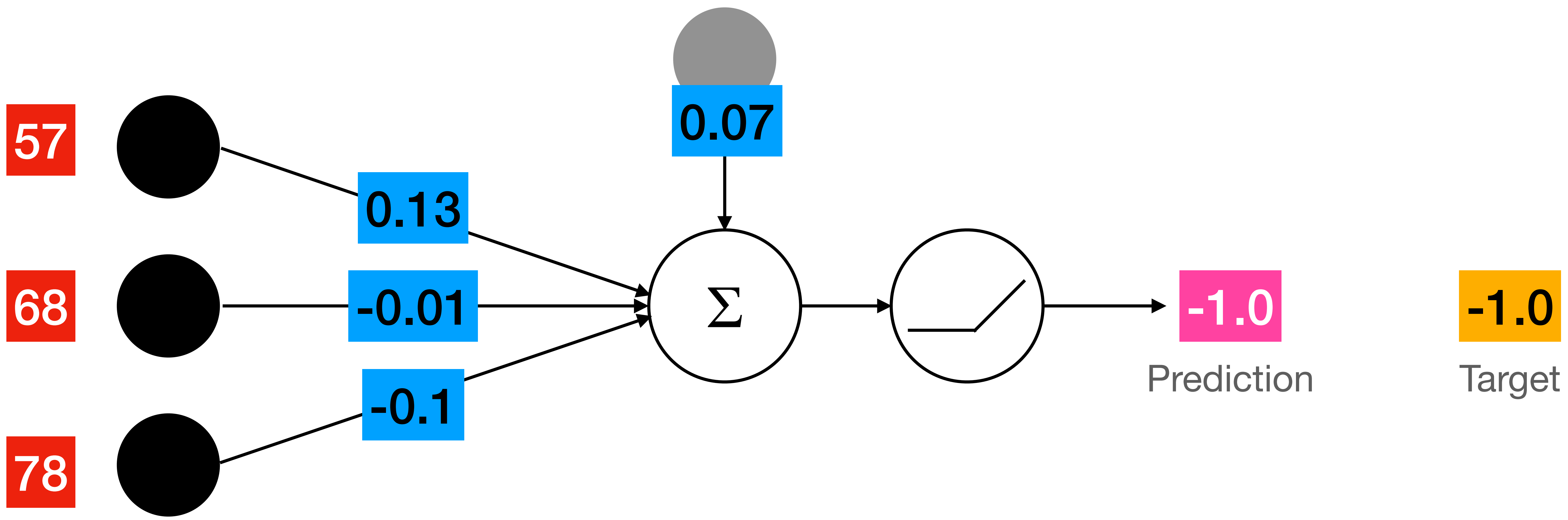
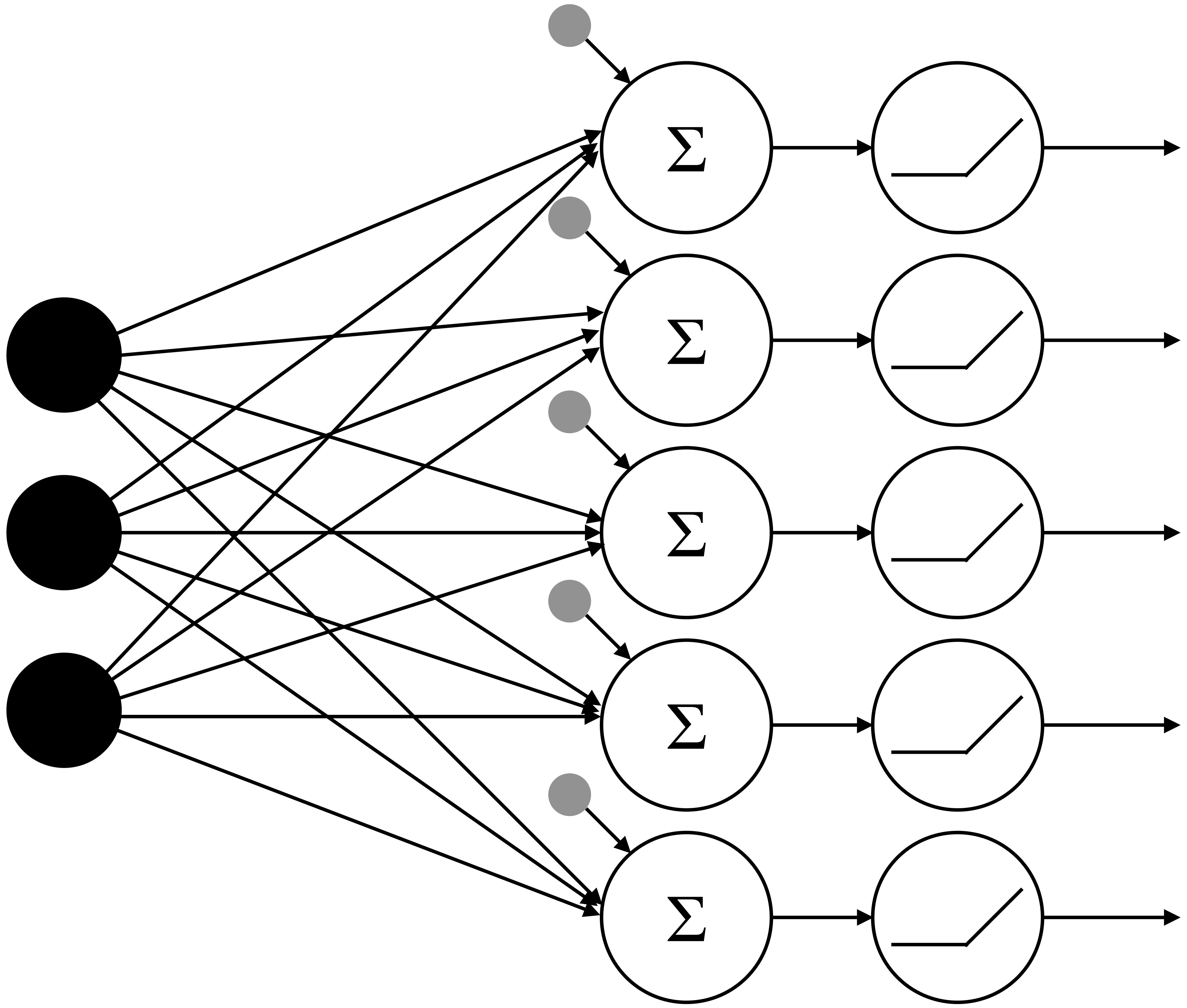


Learning is the process of adjusting the weights & bias so that the prediction is close to the target ***for all training examples***

How does it work?

Modern machine learning with neural networks

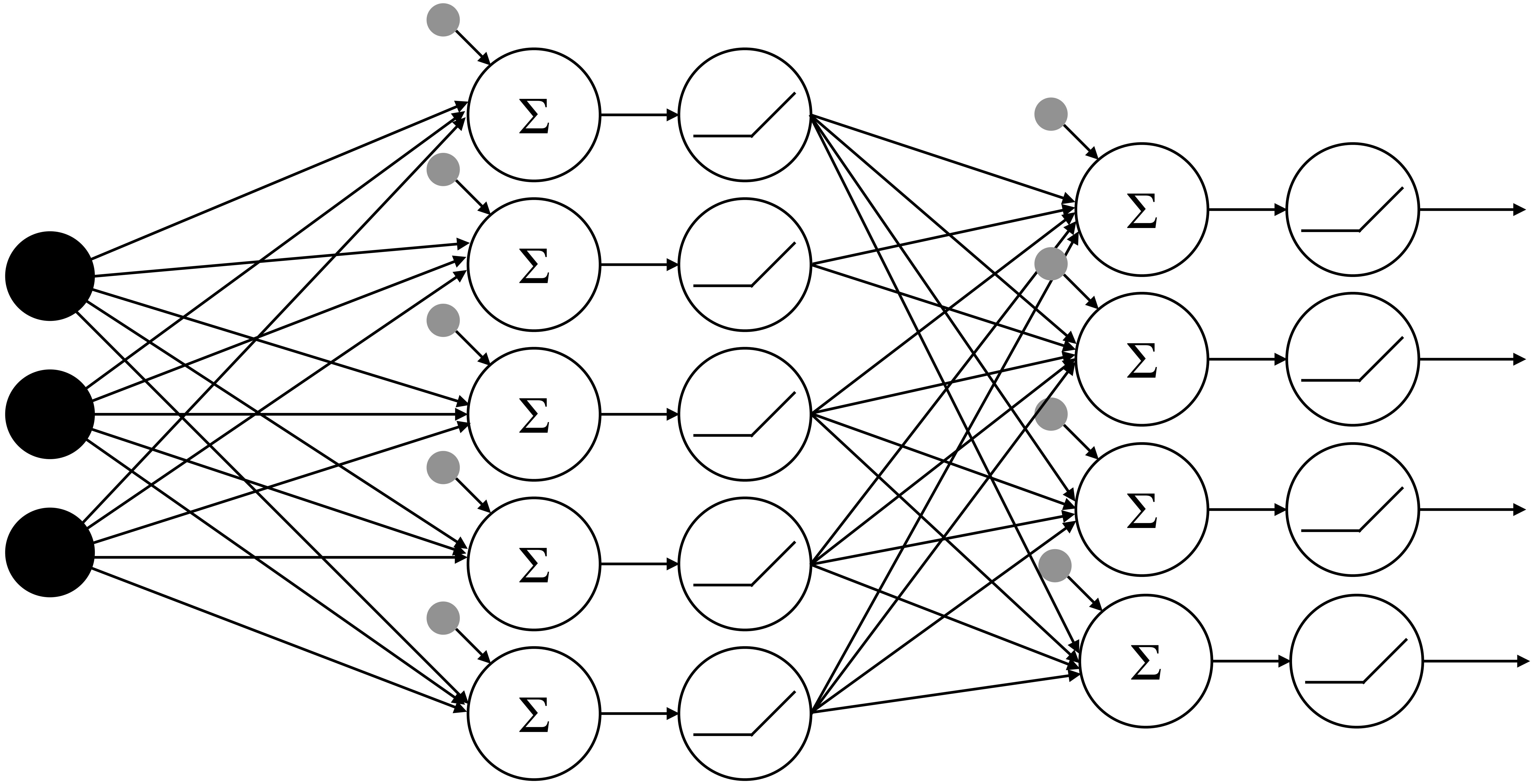
- Almost all modern machine learning is based around a simple idea of an artificial neuron, *which are composed together in width*



How does it work?

Modern machine learning with neural networks

- Almost all modern machine learning is based around a simple idea of an artificial neuron, *which are composed together in width* ***and in depth***



Key terminology

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- (Artificial) Neural Network
- Deep (Neural) Network

Names for different sizes of neural network model

- Convolutional Neural Network / CNN
- Transformer (model)

Different types of model architecture (meaning the neurons are connected in different ways, and weights potentially “shared”)

- Foundation model

Large models trained on massive data that are used as a base for building applications

Problems of learning

- Typically huge amounts of data needed (usually scaling with the complexity of the learning machine)
    - For supervised learning this needs to be manually labelled
- Machine learning is very much an empirical science; you need to try lots of things and see what works best for your problem

What's the best model?

CNNs versus Transformers versus …

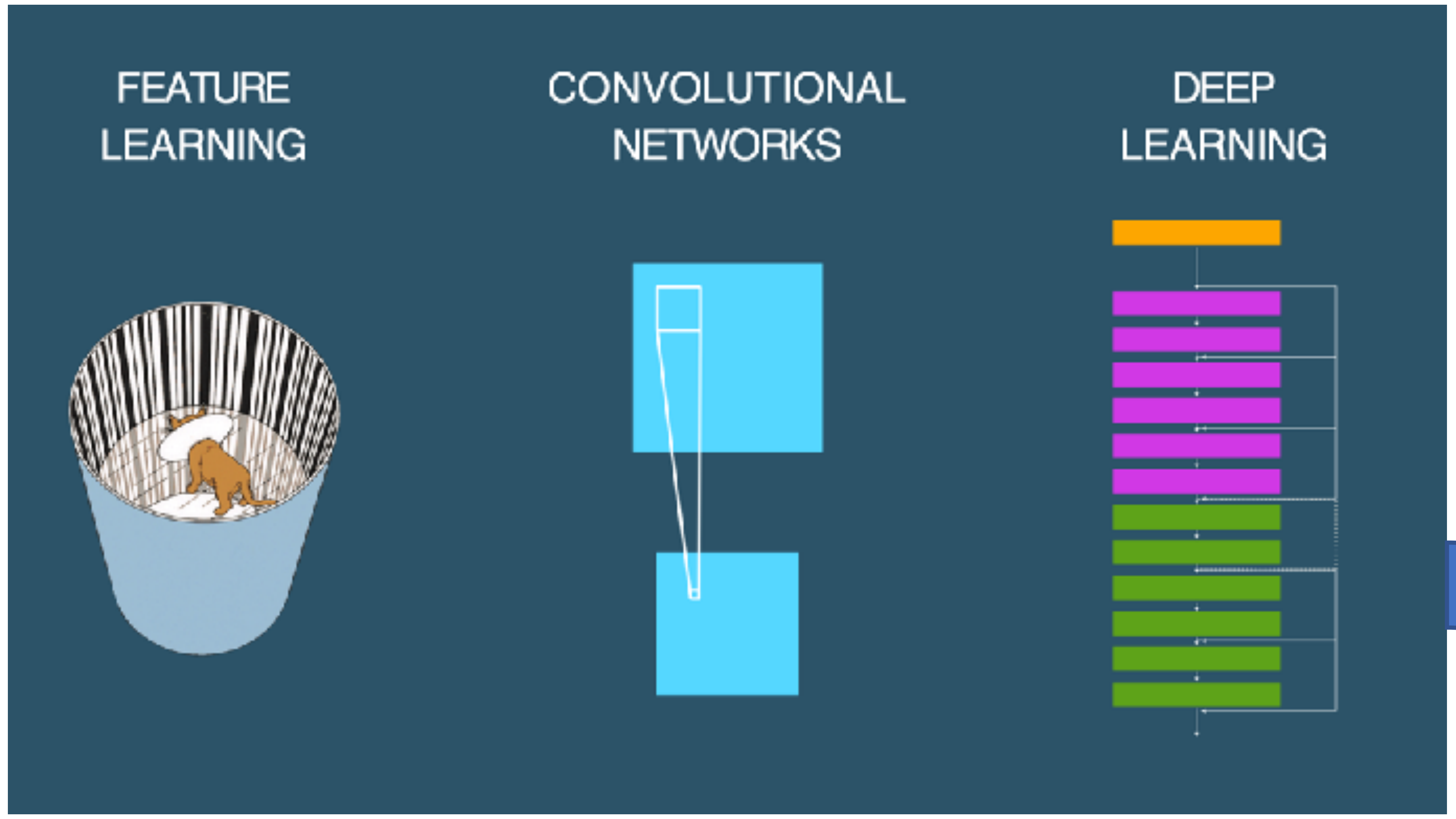
- No simple answer; it depends on the data and the problem
- On visual data:
    - Transformers trained with lots of data can learn large-scale dependencies
    - Traditional CNNs were limited to looking locally
        - But recent CNN advancements compete with transformers (e.g. https://openreview.net/forum?id=fvui3I49nO)

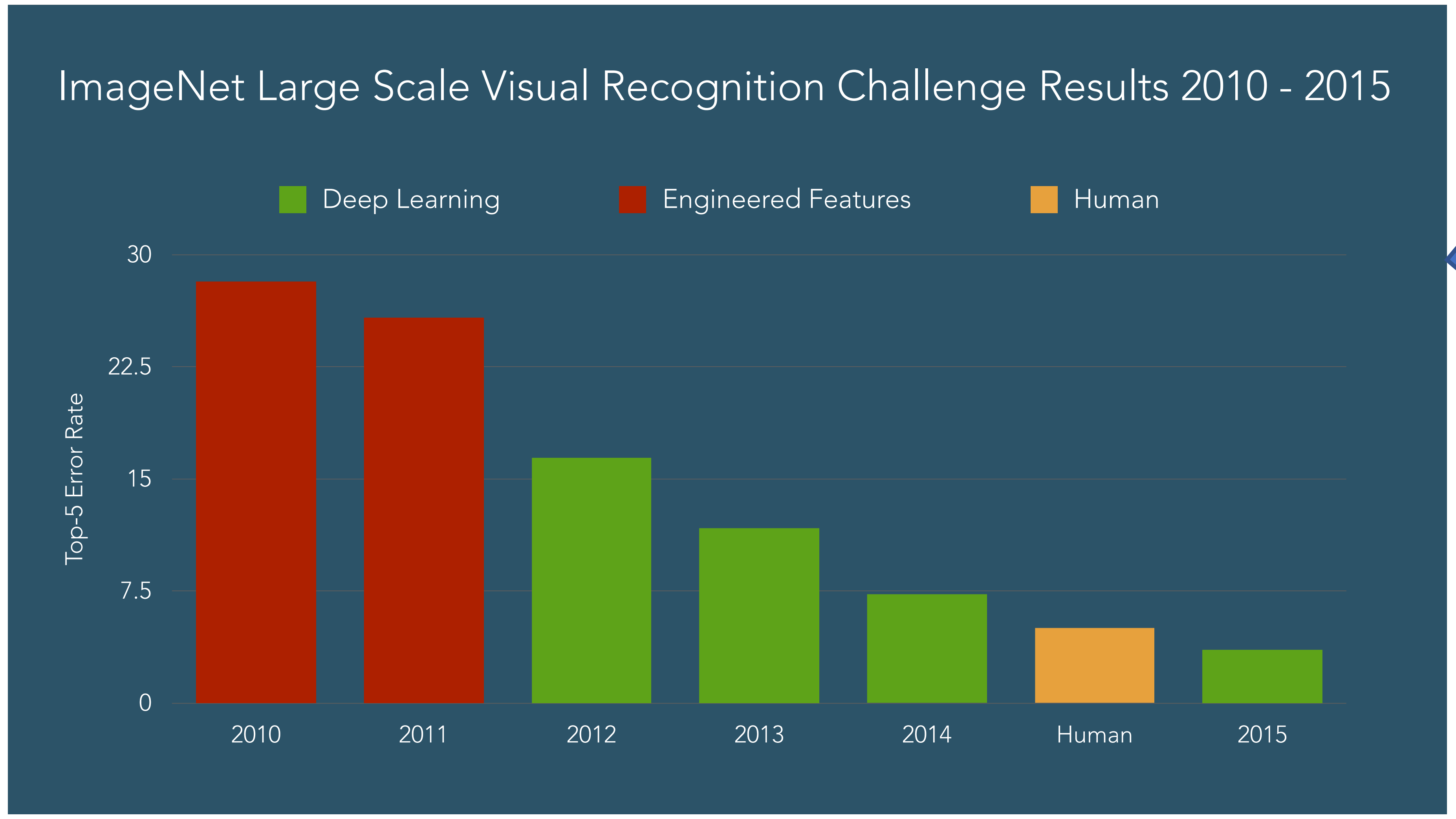
Why should we care about machine learning?

What can we do with geospatial data and machine learning?

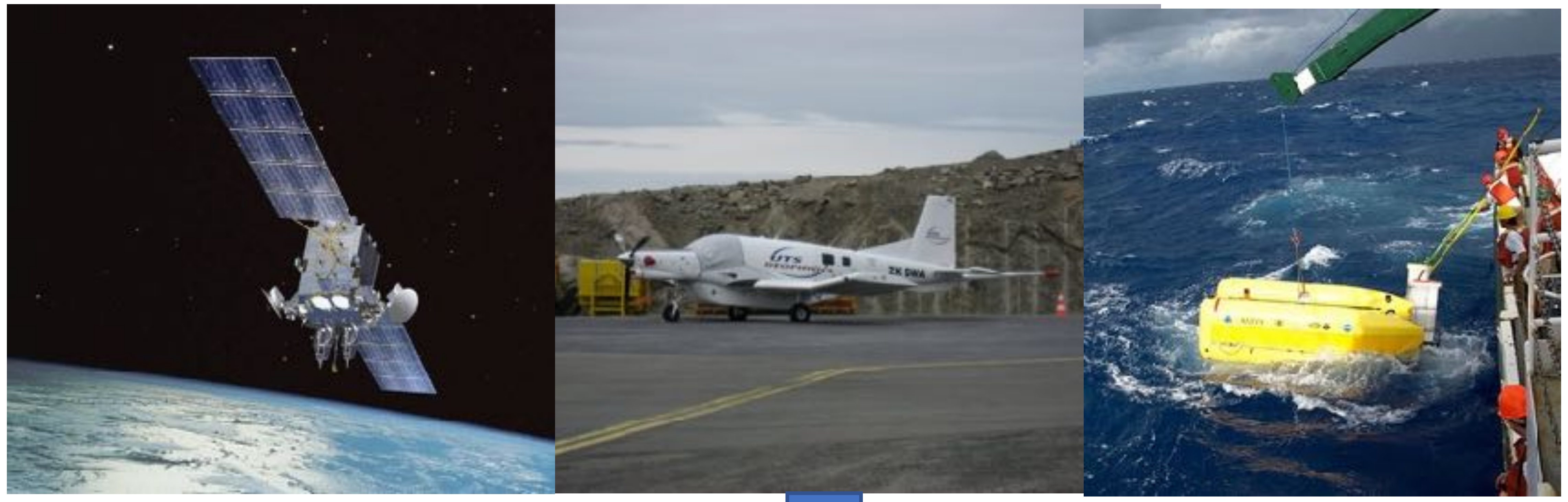
What are the challenges?

Why should we care?

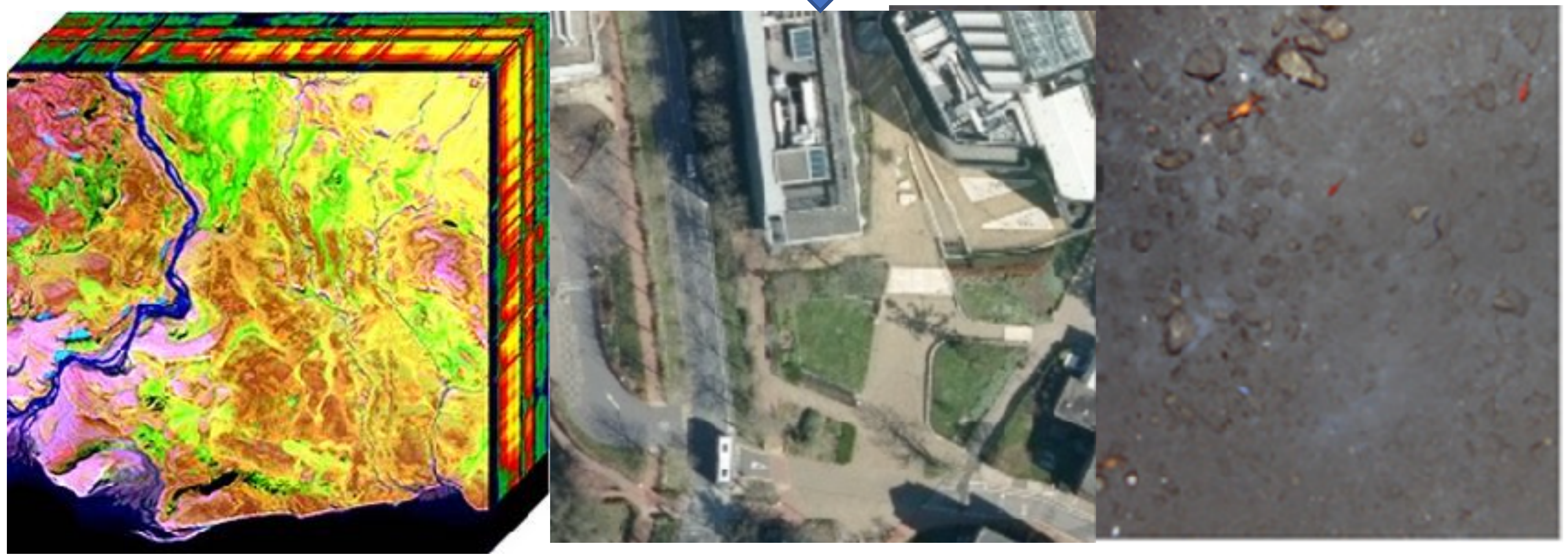




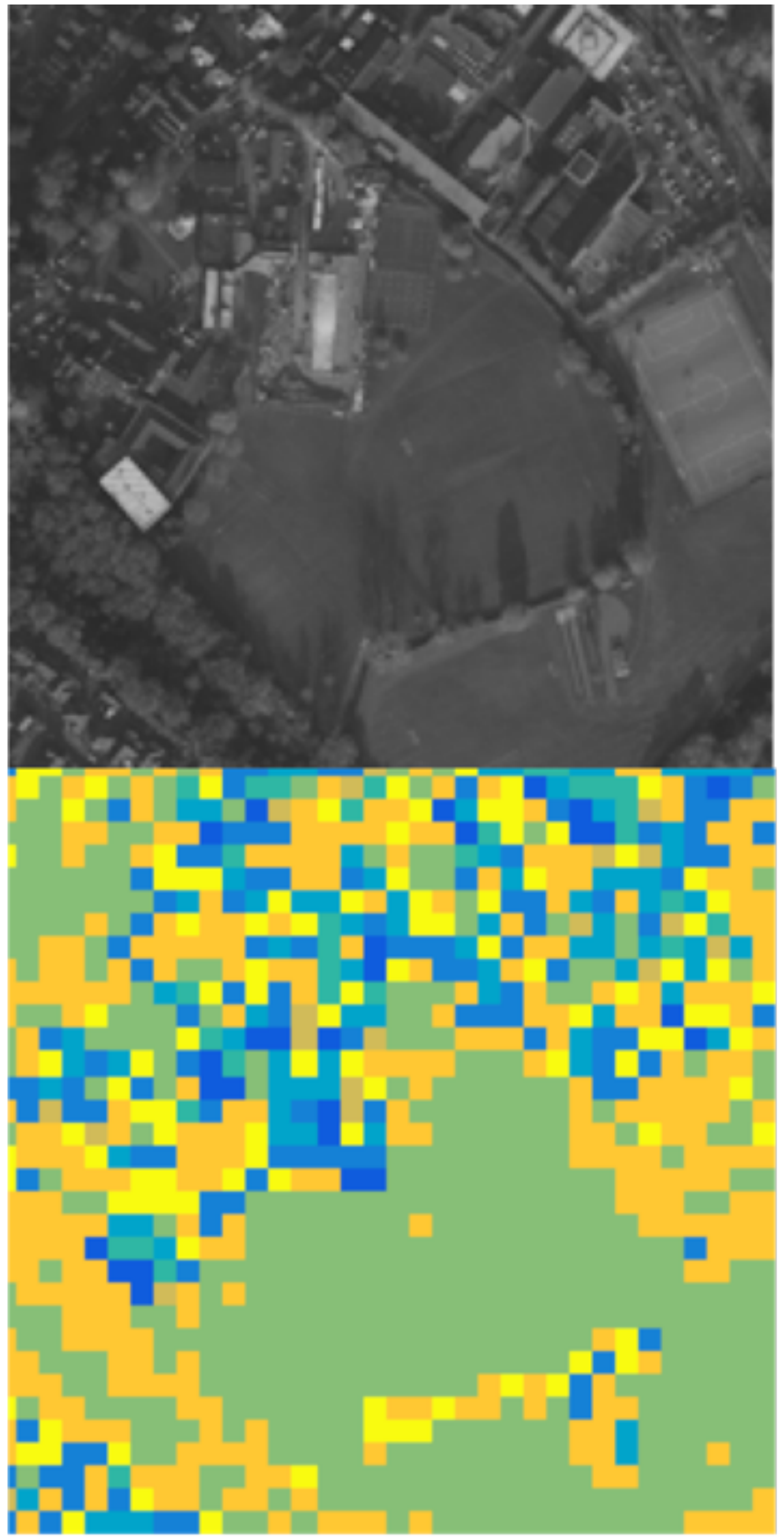
Superhuman performance

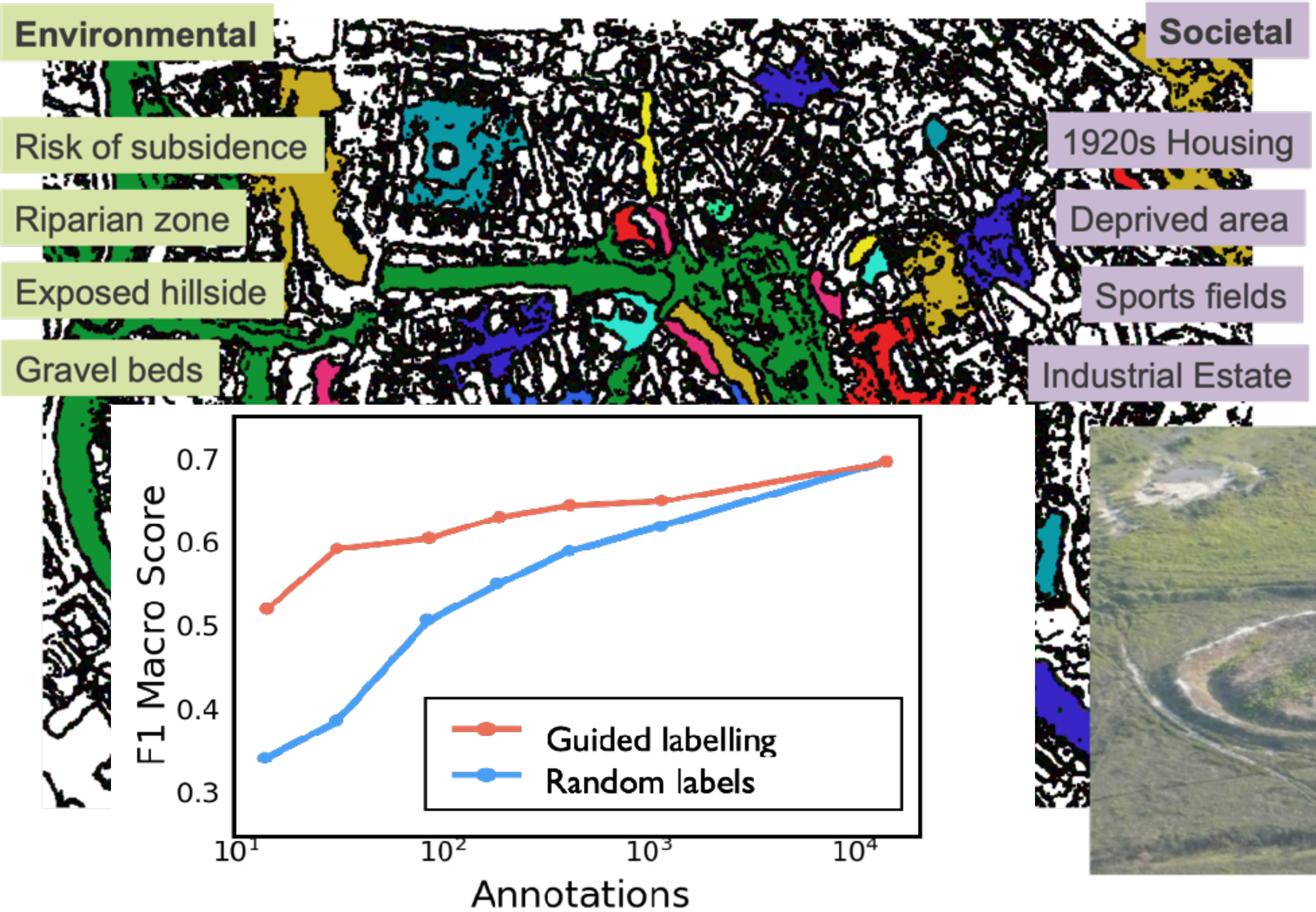


Remote sensing data is growing at an immense rate

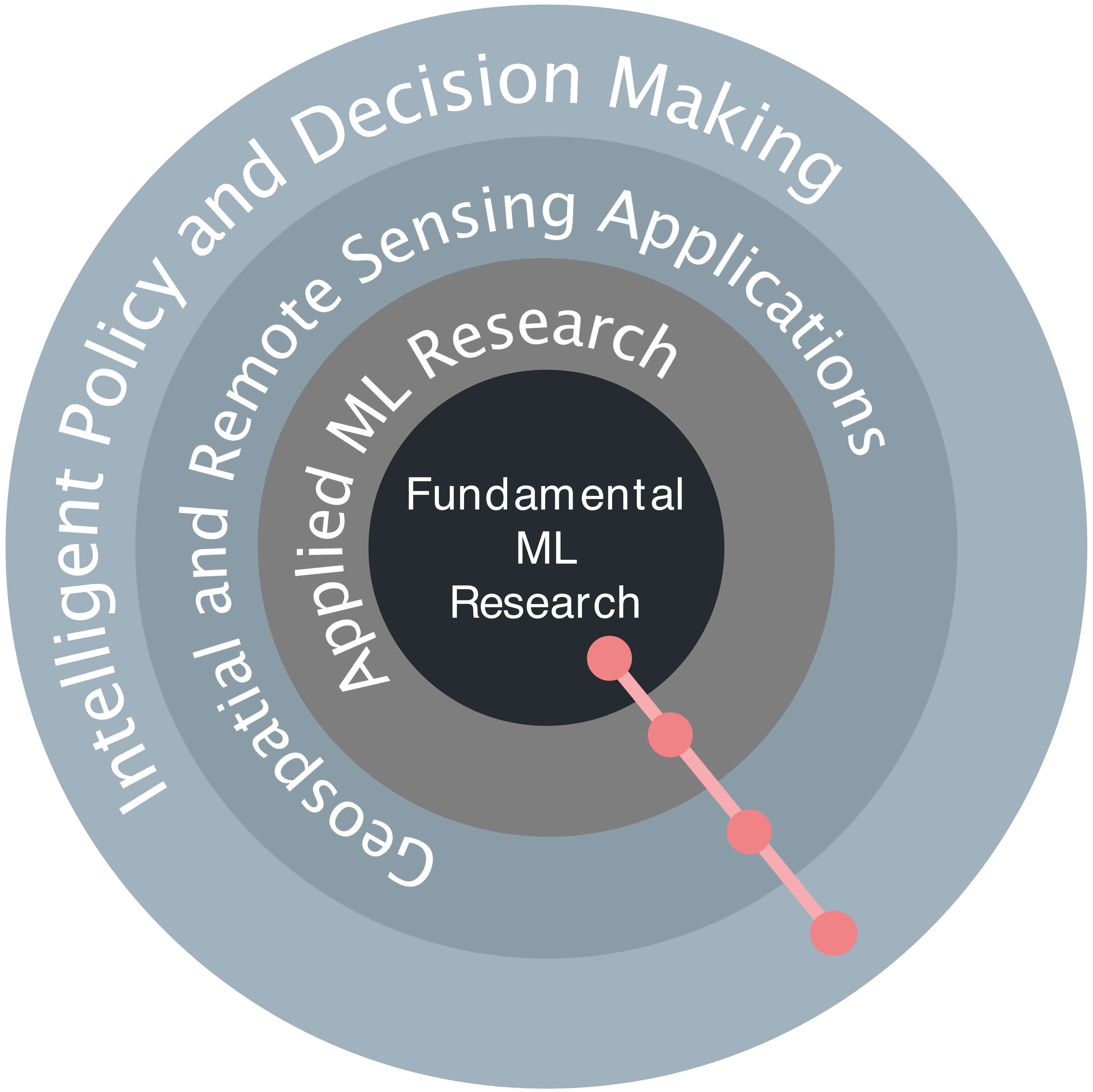


Efficiently Learning From Remote Sensing Imagery



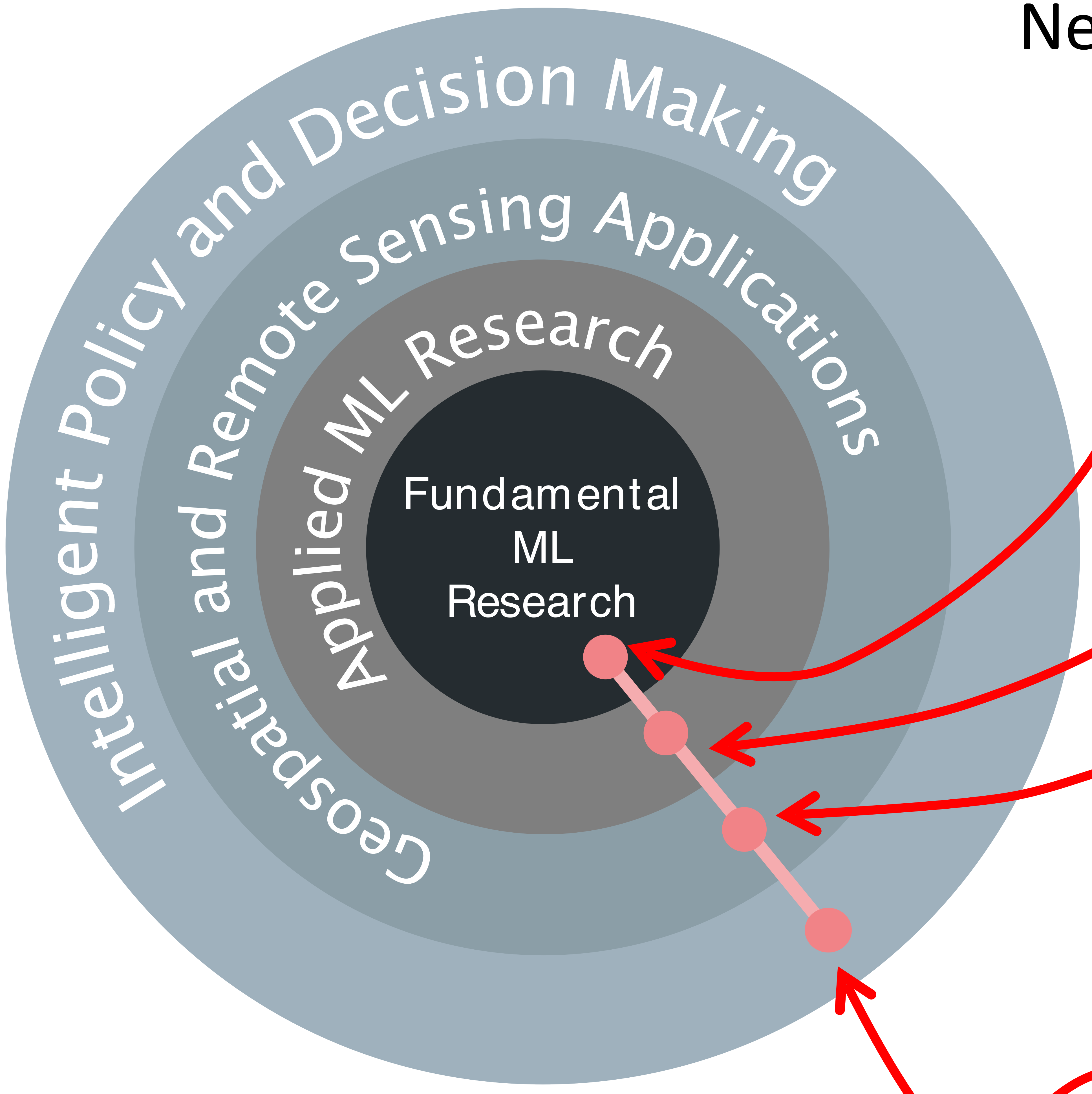


What are the Challenges?



- Many challenges!
  - Fundamental research questions:
    - model/algorithm/optimisation design through to domain-specific problems in utilising learning machines to solve tasks
  - People challenges:
    - Finding a common ground (and language)
    - Knowledge transfer
    - Skills transfer
  - Ethical challenges:
    - Potential for misuse or control, etc
    - Accidental "personal" data leakage

Example challenges:



New methods for self-supervised pretraining

Transfer of domain knowledge into priors and appropriate inductive biases

Data cleaning, munging, etc.

Making enough labelled data for training

Communicating information, understanding limitations and making good decisions

Geospatial ML Research Examples at Southampton

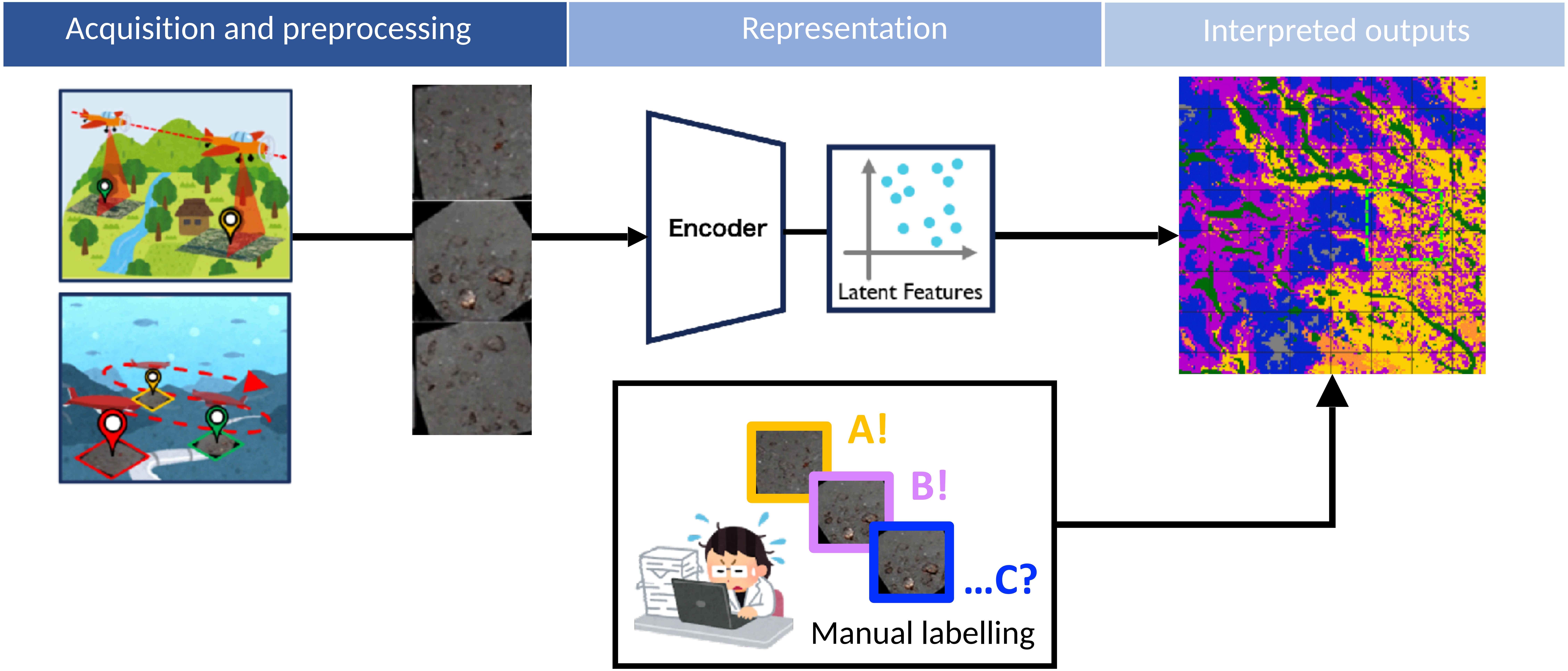
University of Southampton

Learning with less human labelling effort

Blackbox machine learning – Supervised by examples

Challenges

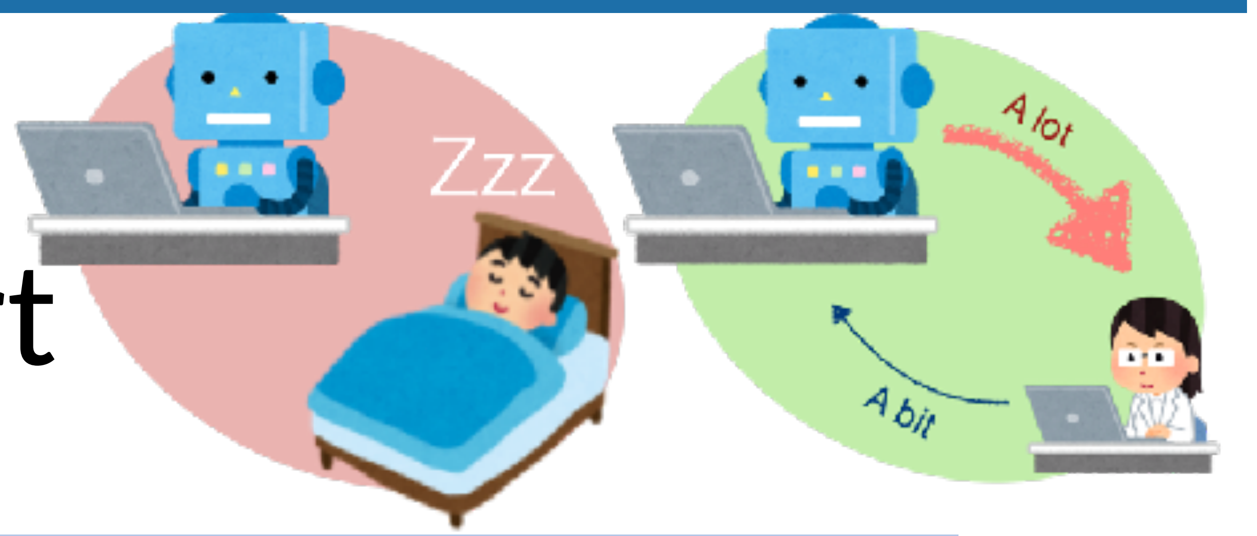
- ✓ Lots of human effort
- ✓ Limited transfer across datasets



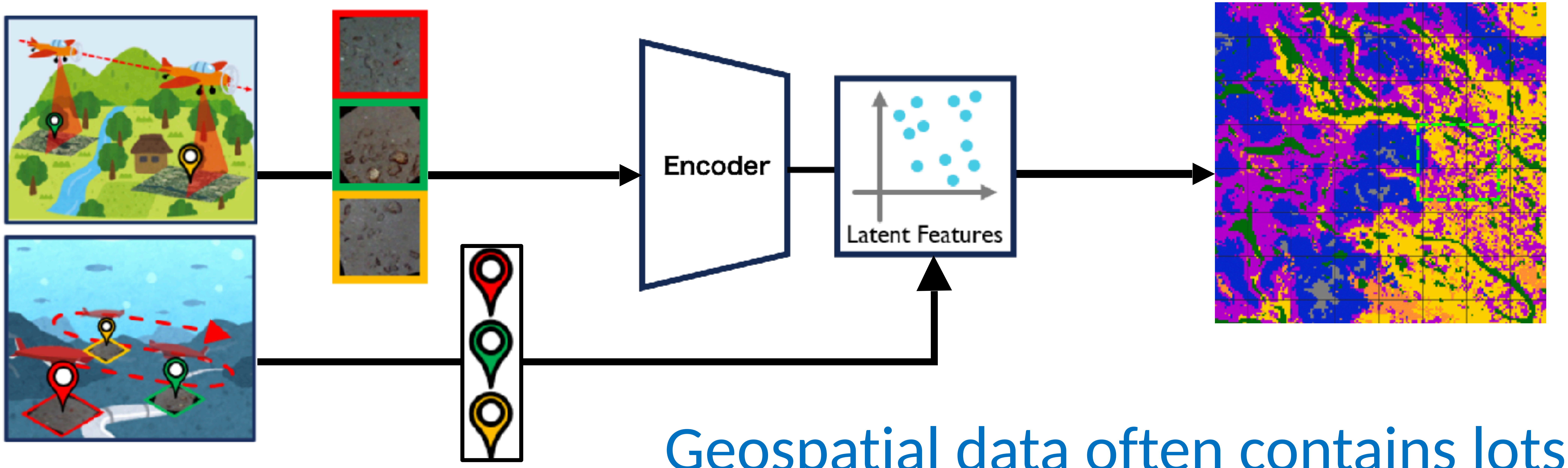
Geospatial self-supervision

Introduce domain understanding

- ✓ Eliminate, minimise and efficiently guide human effort



Acquisition and preprocessing	Representation	Interpreted outputs



Geospatial data often contains lots of similarities that can be exploited

Yamada et al., J. Field Robotics (2021)
Yamada et al., Trans. PAMI (2022)
Yamada et al., Field Robotics (2022)

Geospatial self-supervision

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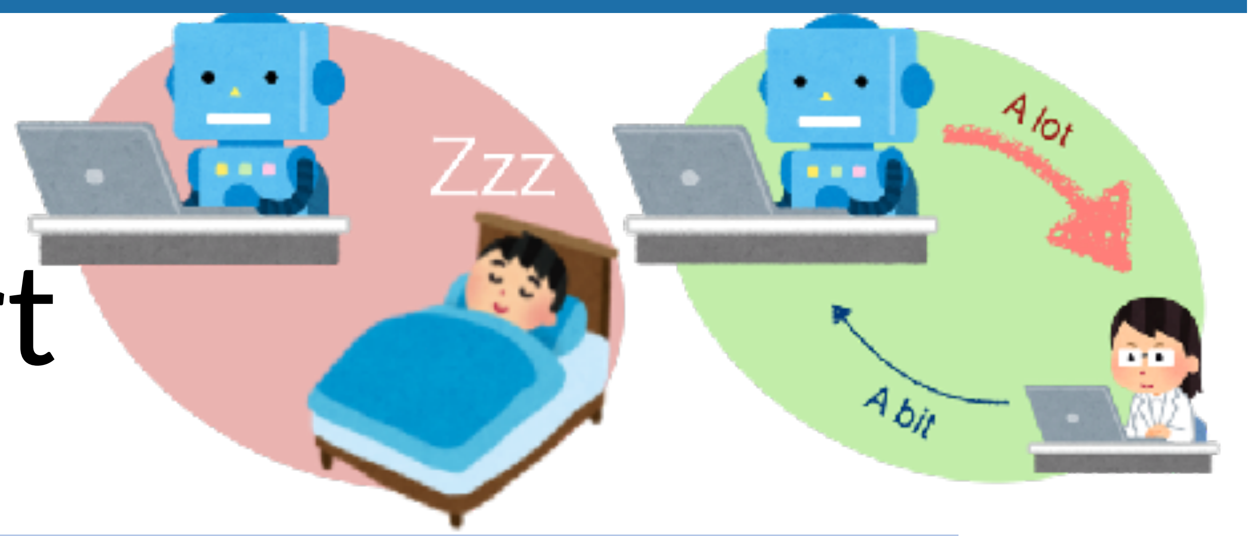

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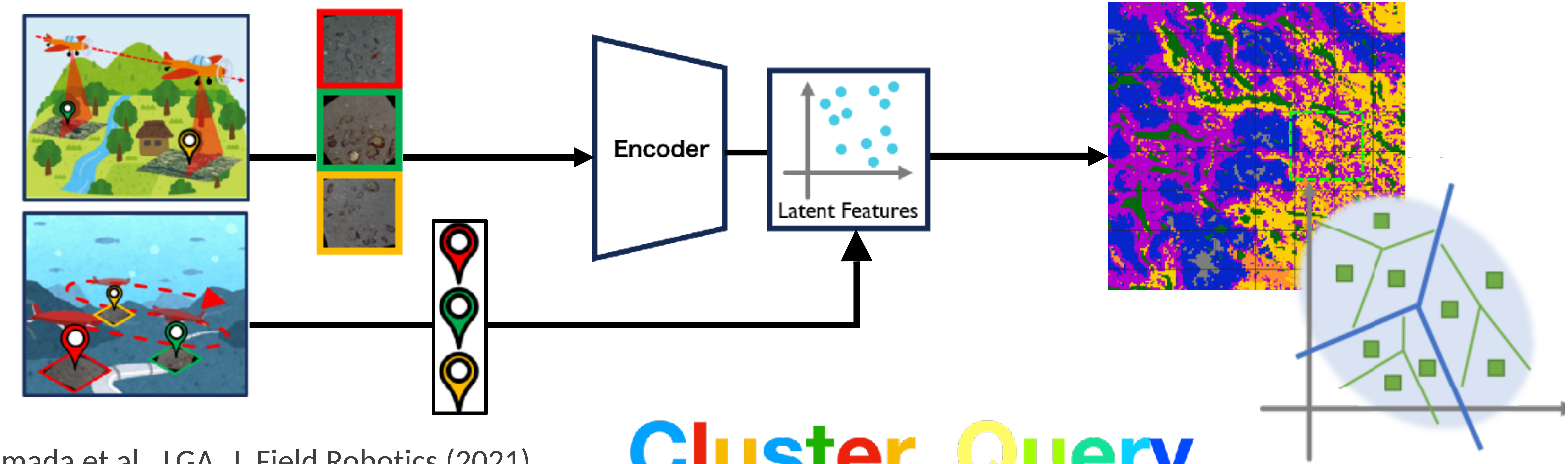

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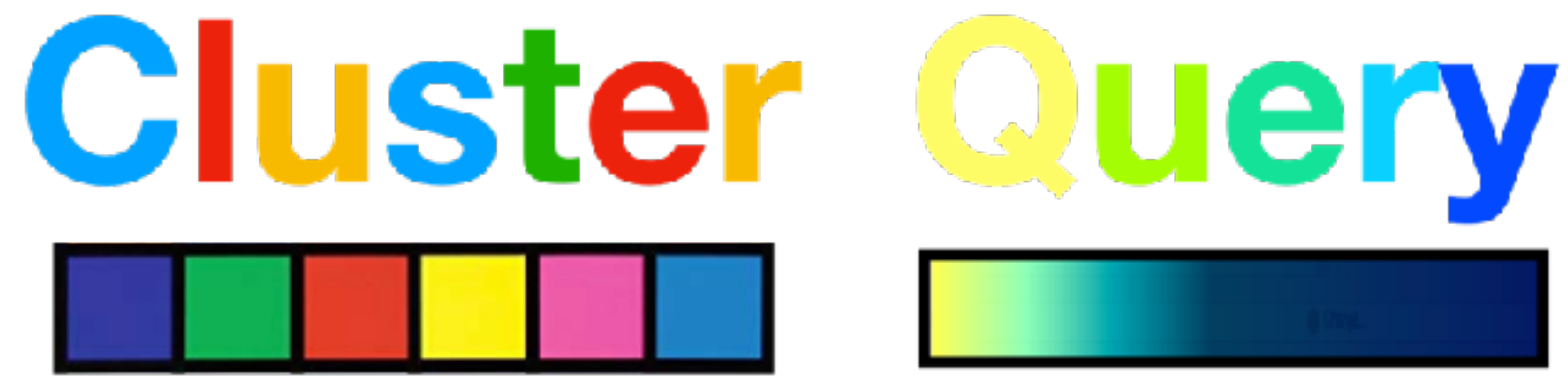
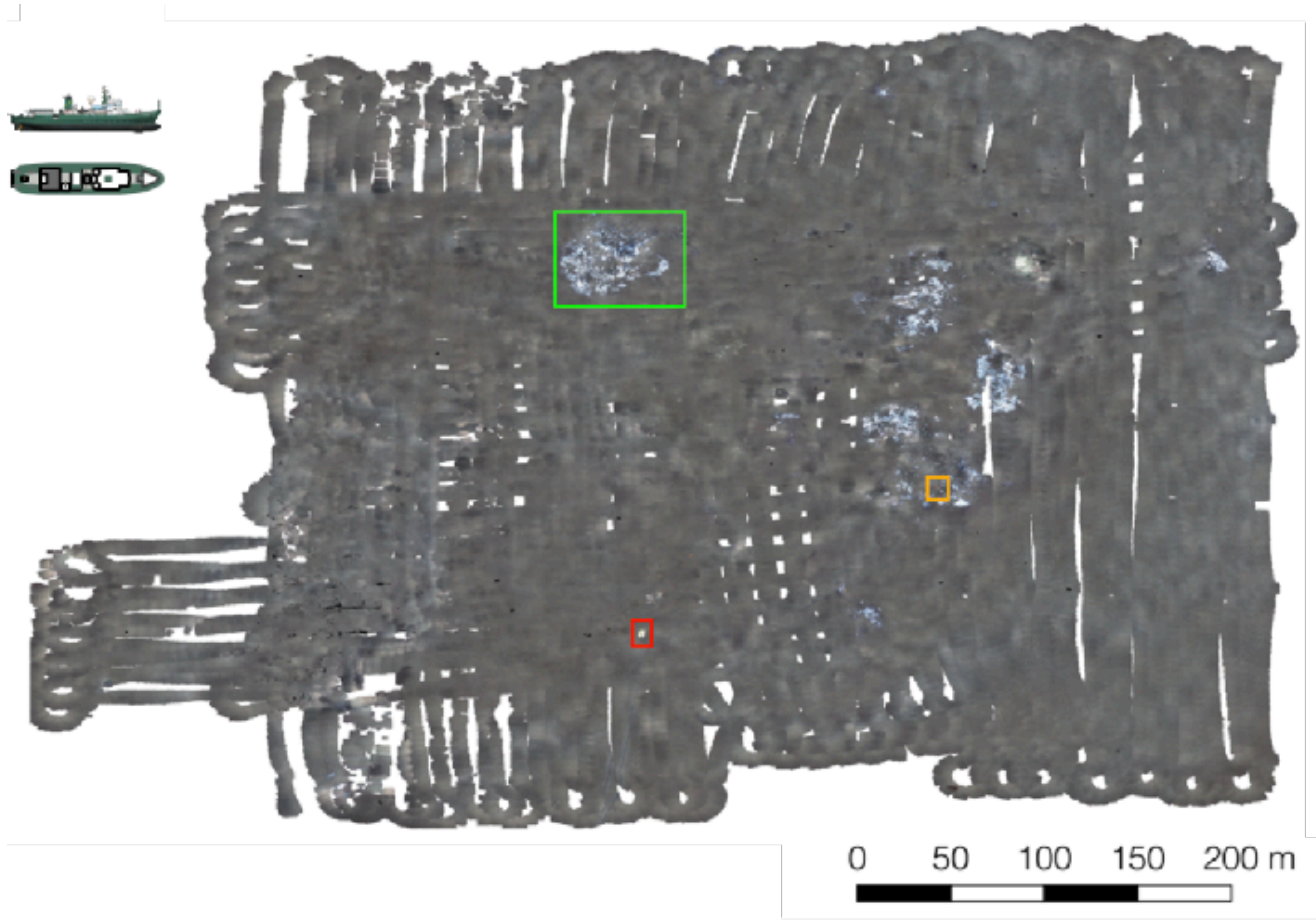
Yamada et al., GeoCLR, Field Robotics (2022)



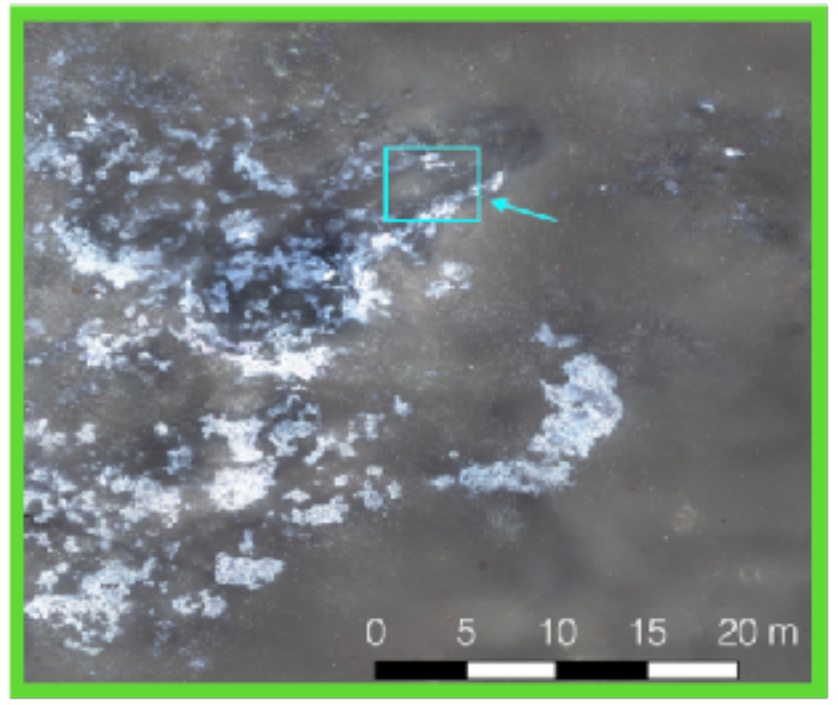
Representative image ID

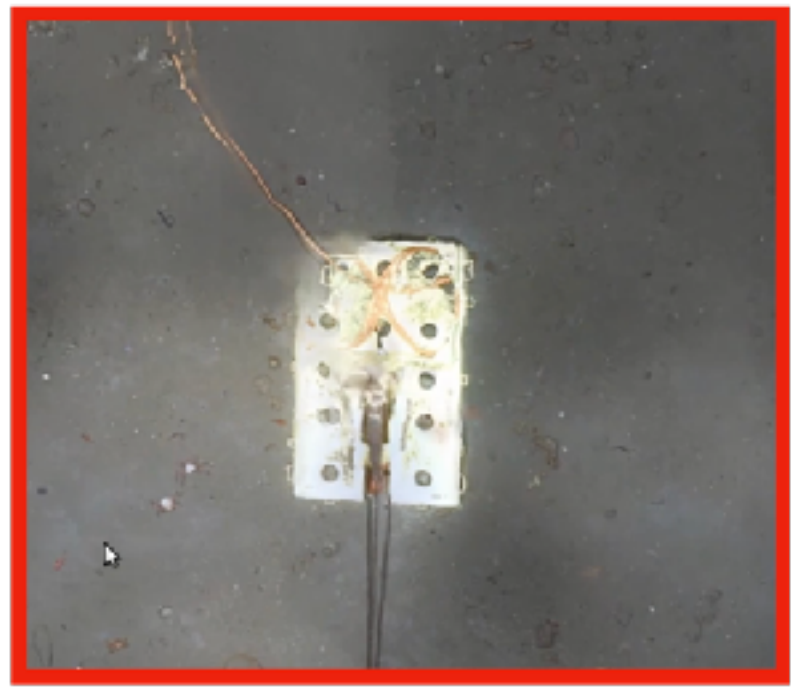
Seafloor habitats and communication infrastructure

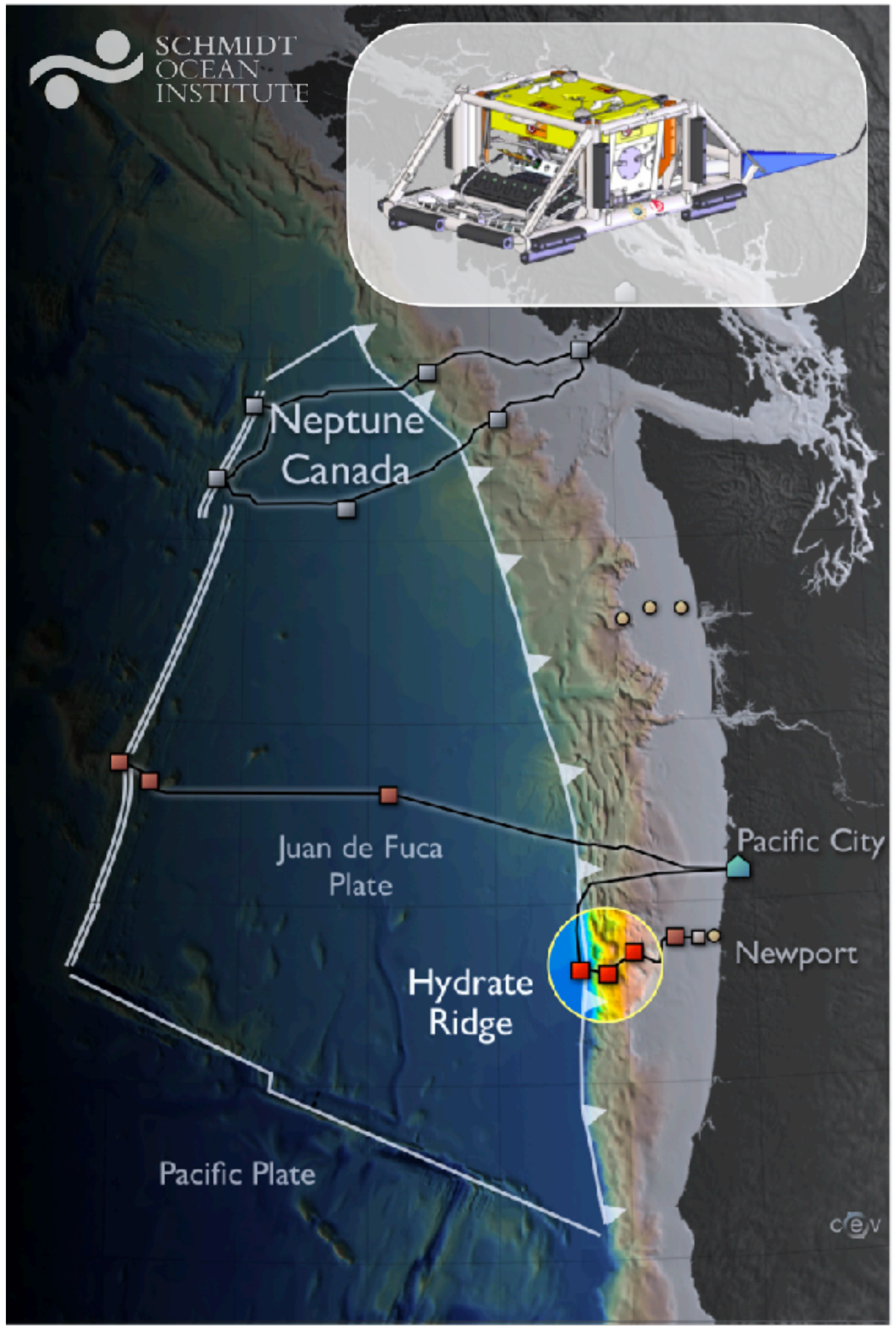
Southern Hydrate Ridge



Boldrewood campus to scale







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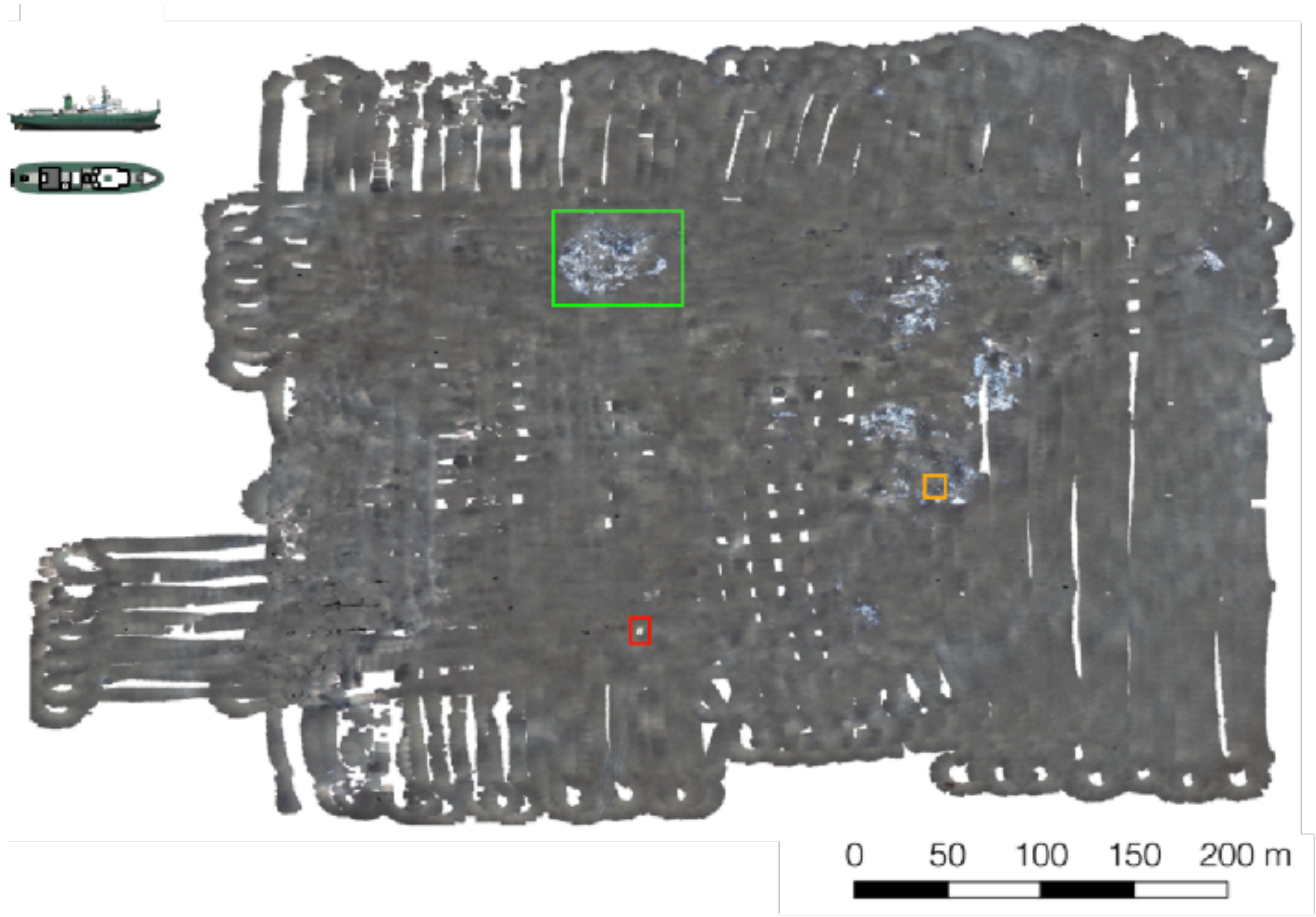

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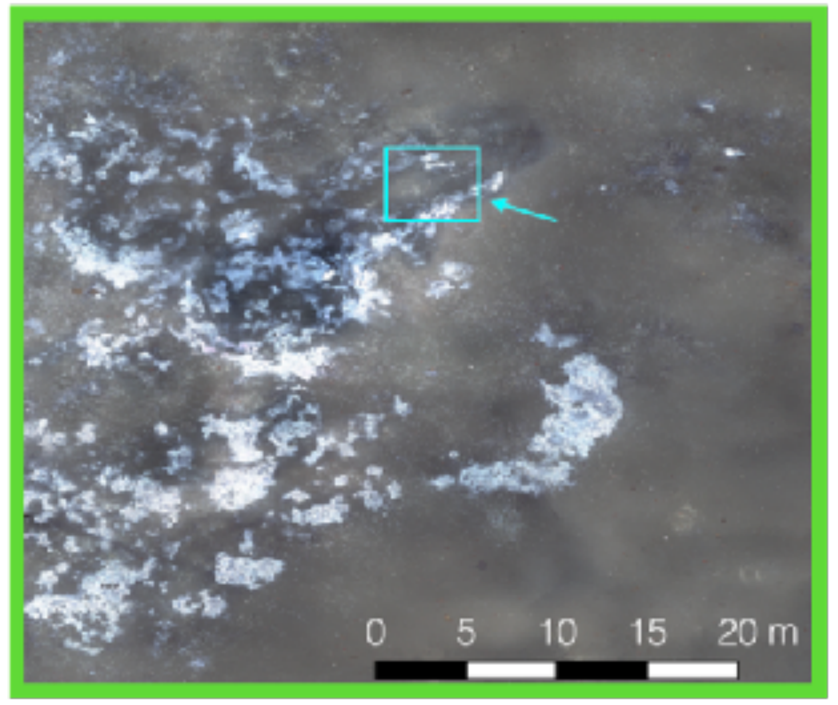
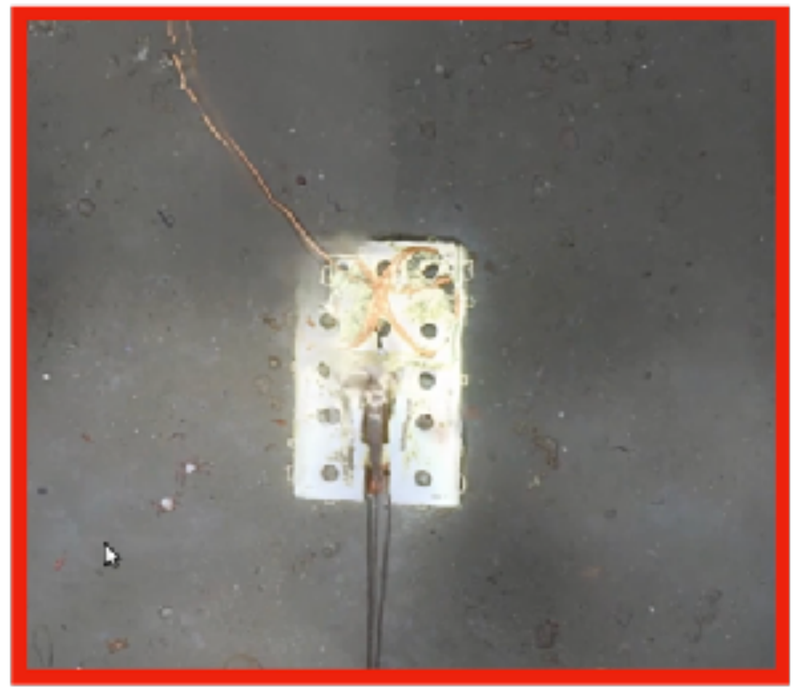
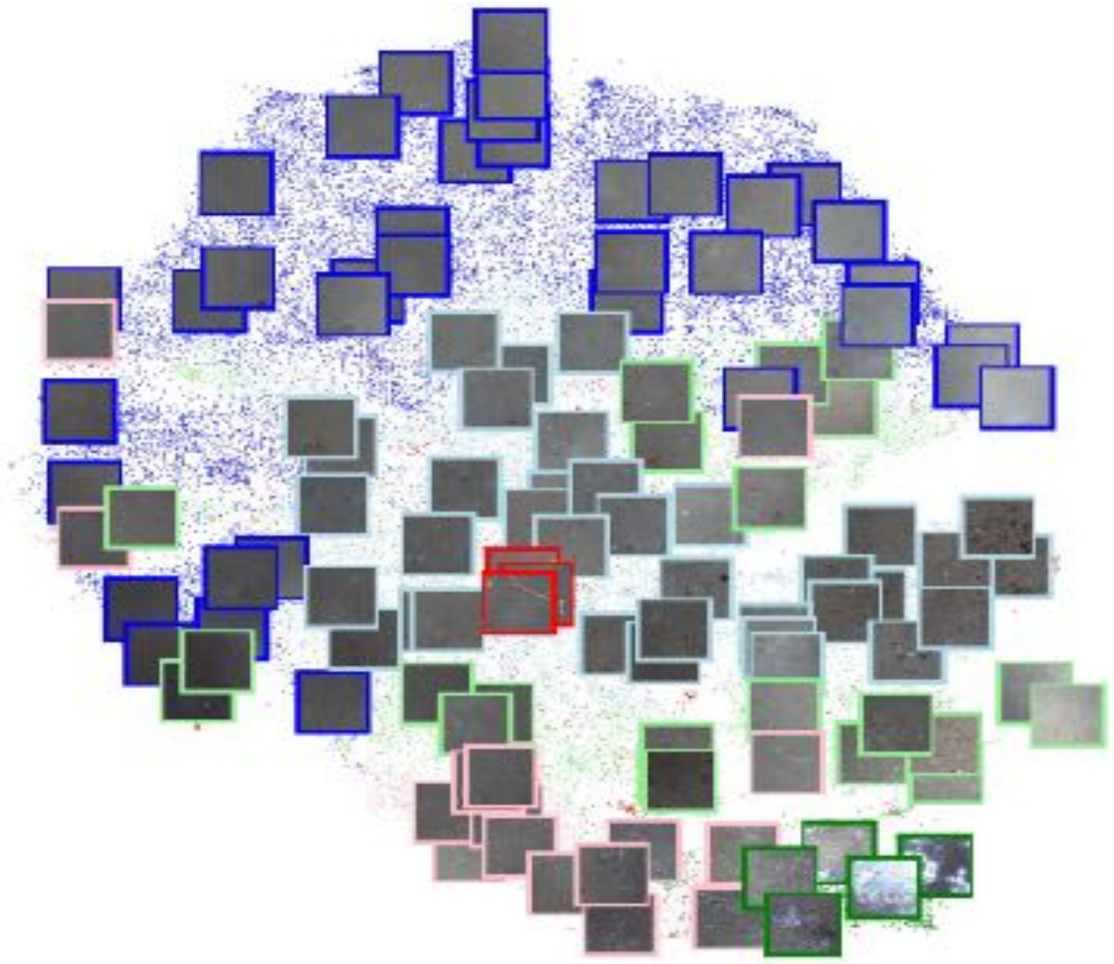


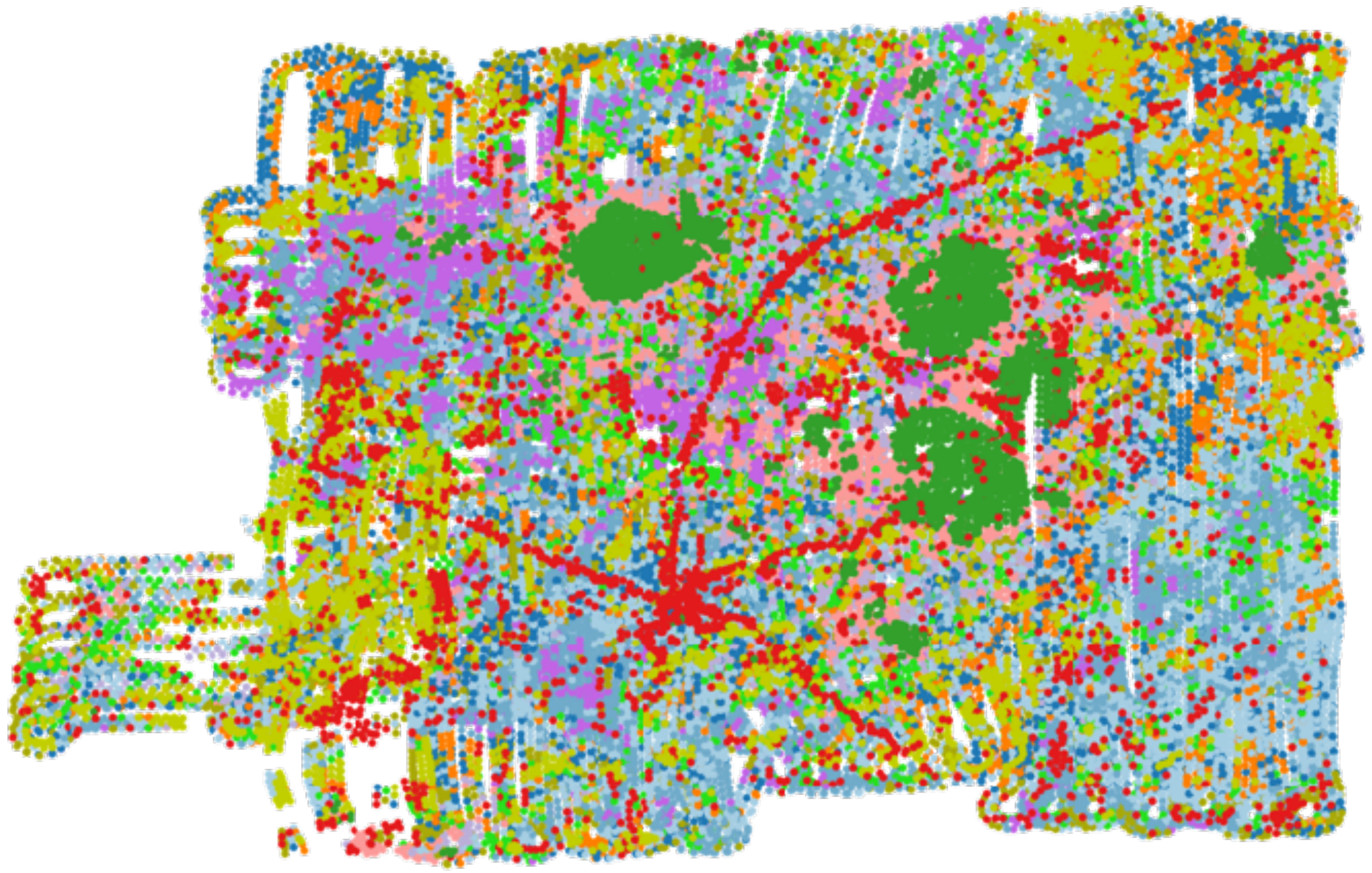


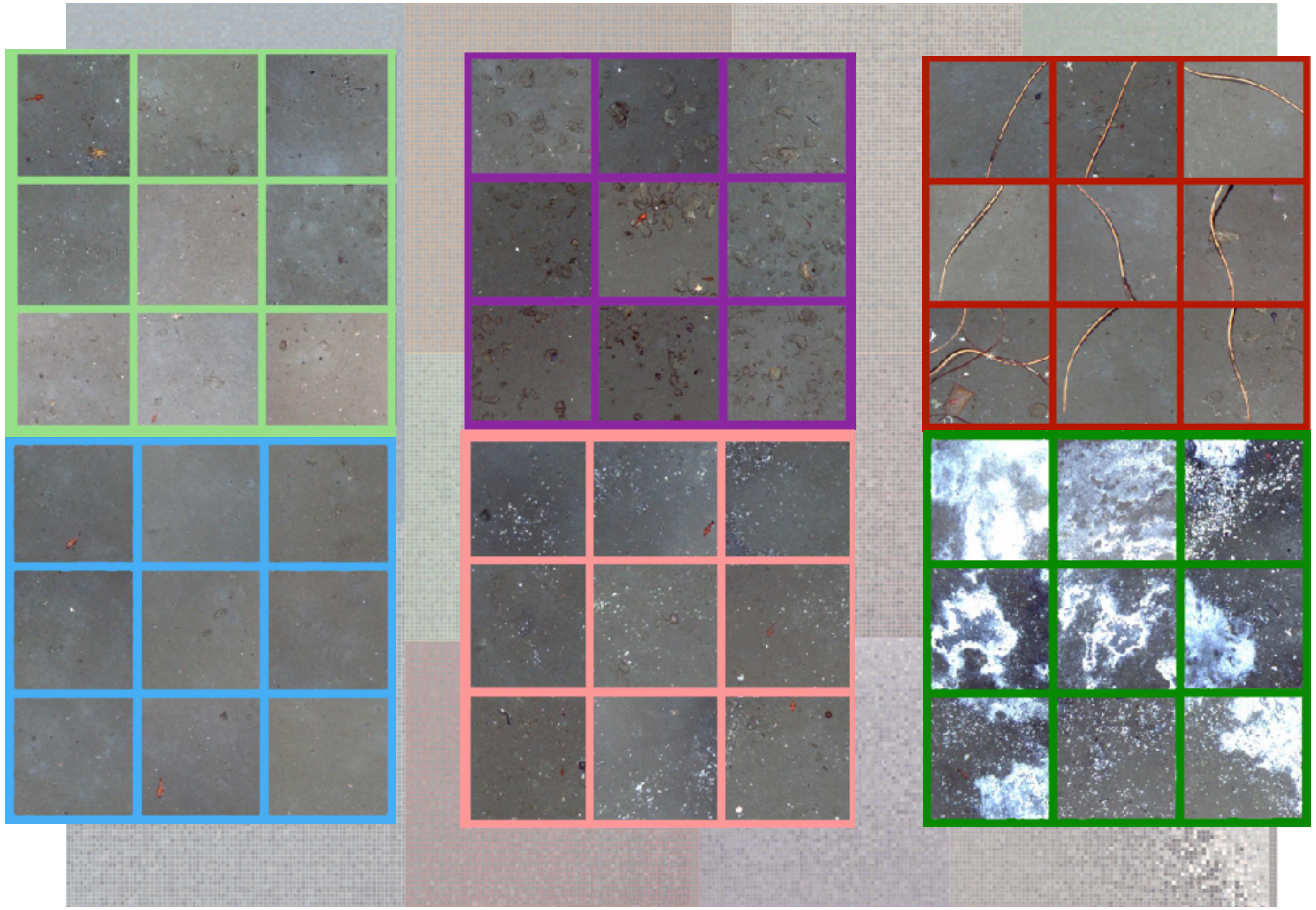
Rapid (same day) interpretation

Cluster, query and representative image ID



Left: T-SNE Feature space
Right: Representitive images
Below: Cluster Map





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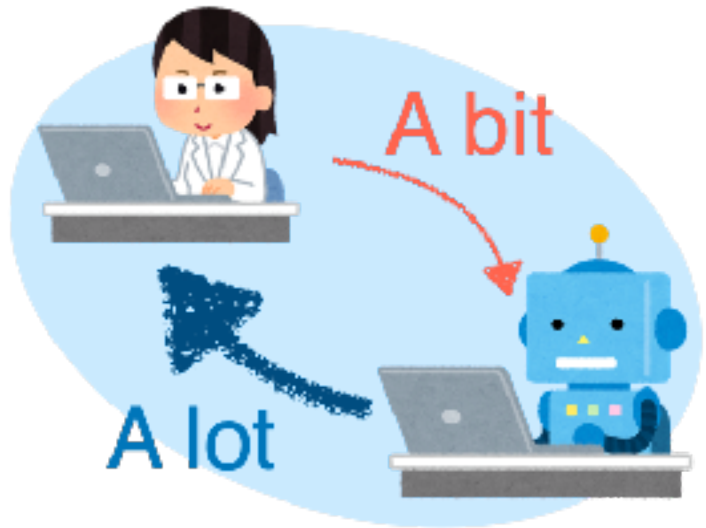
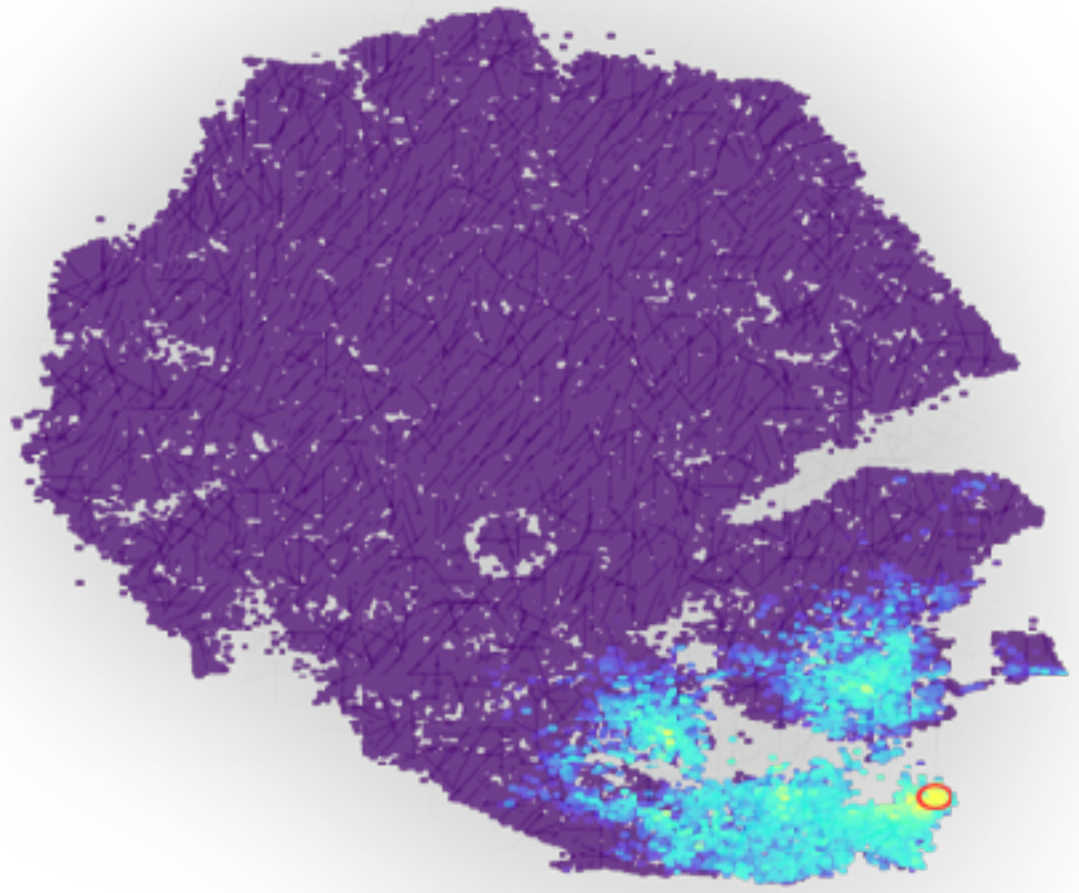
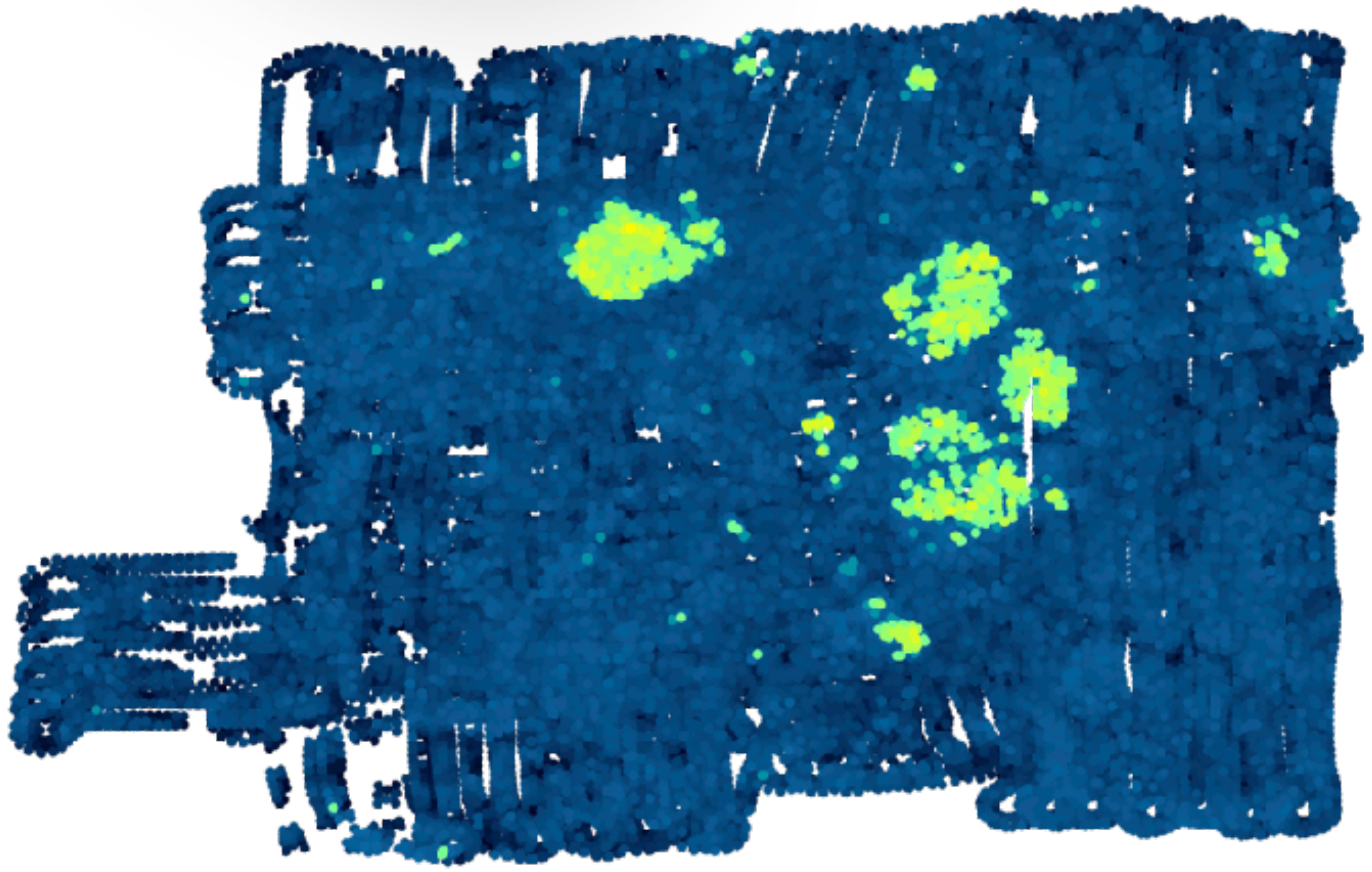
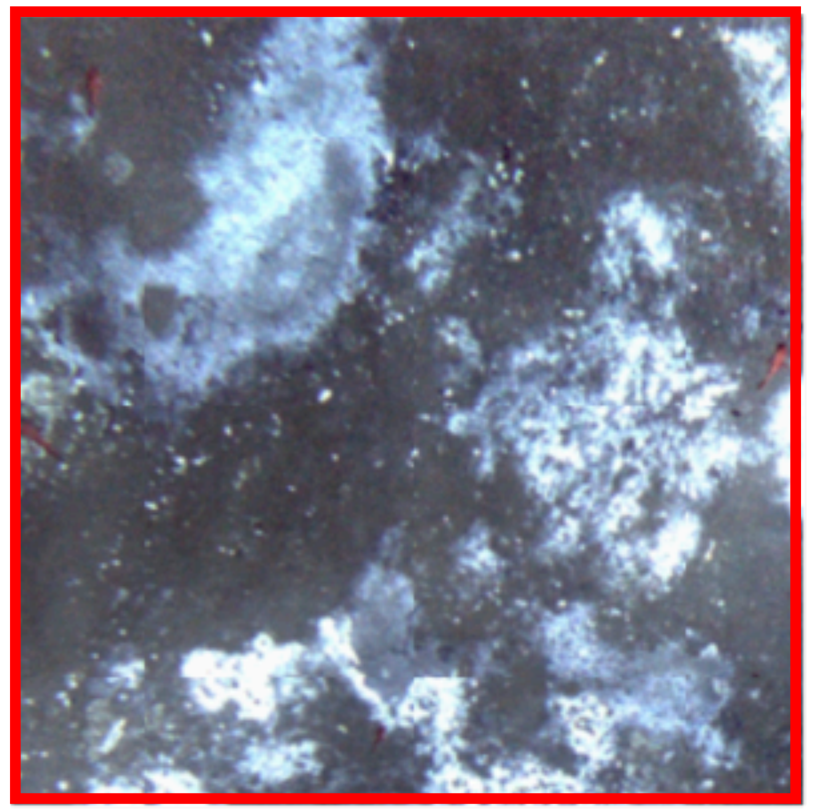




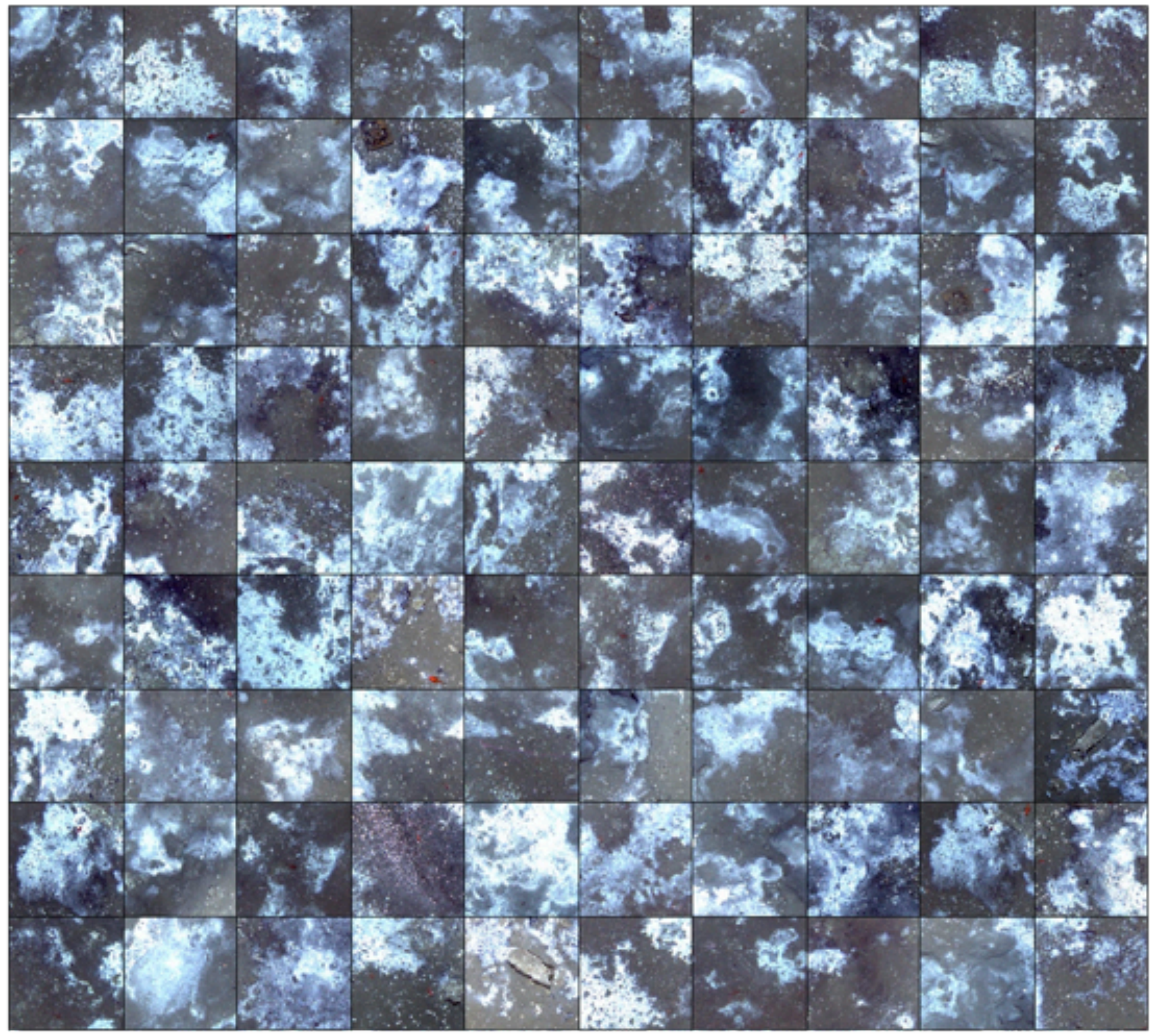
Left: T-SNE Feature space
Right: Query and return
Below: Similarity Map



Query image



Similarity ranked return



Similarity

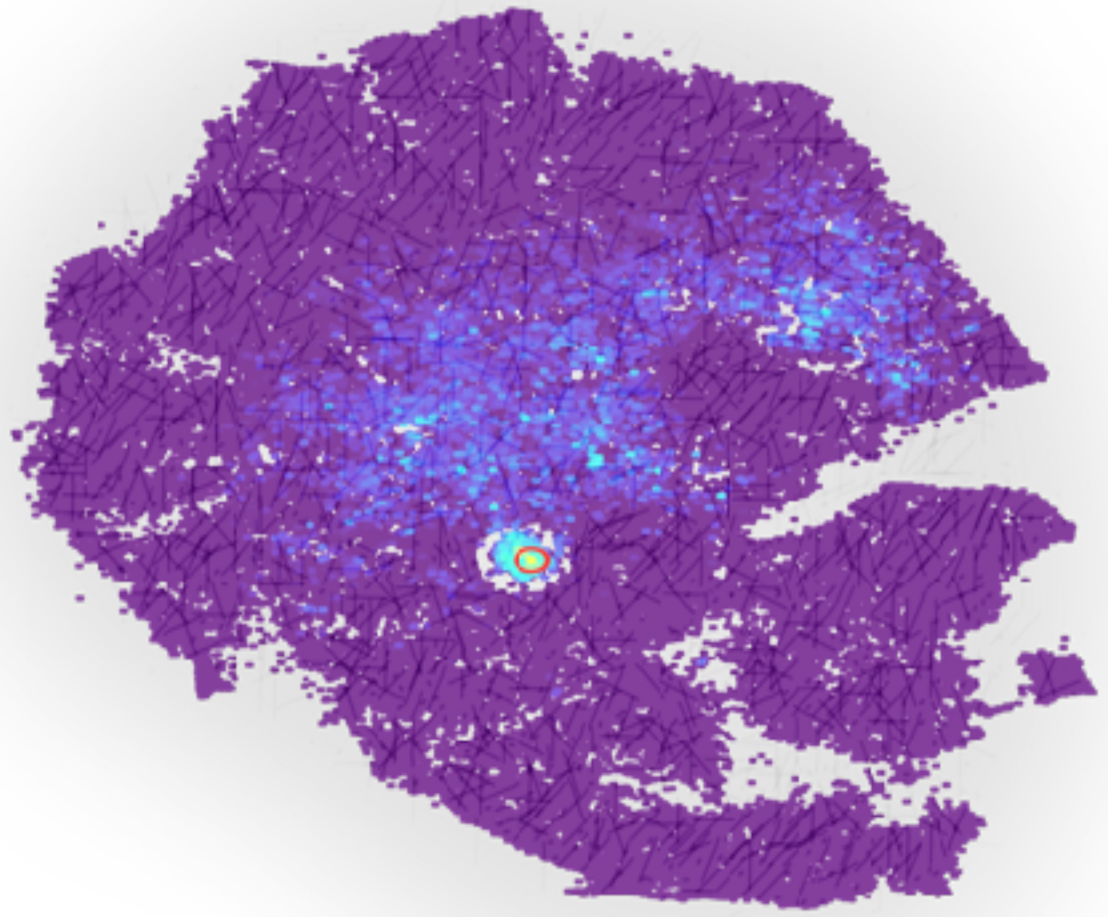
High

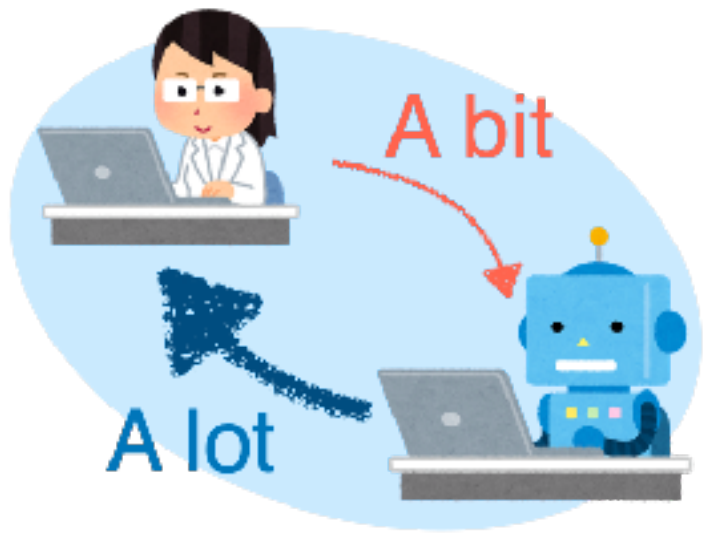
Low

NB: Flexible query return is a milli-second operation

Rapid (same day) interpretation

Cluster, query and representative image ID





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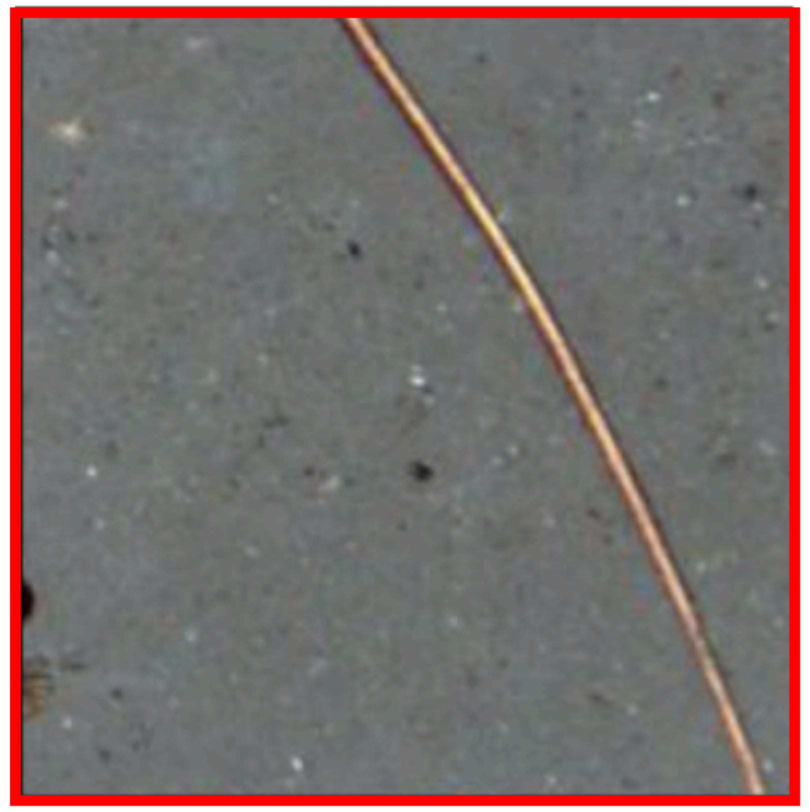
Query image



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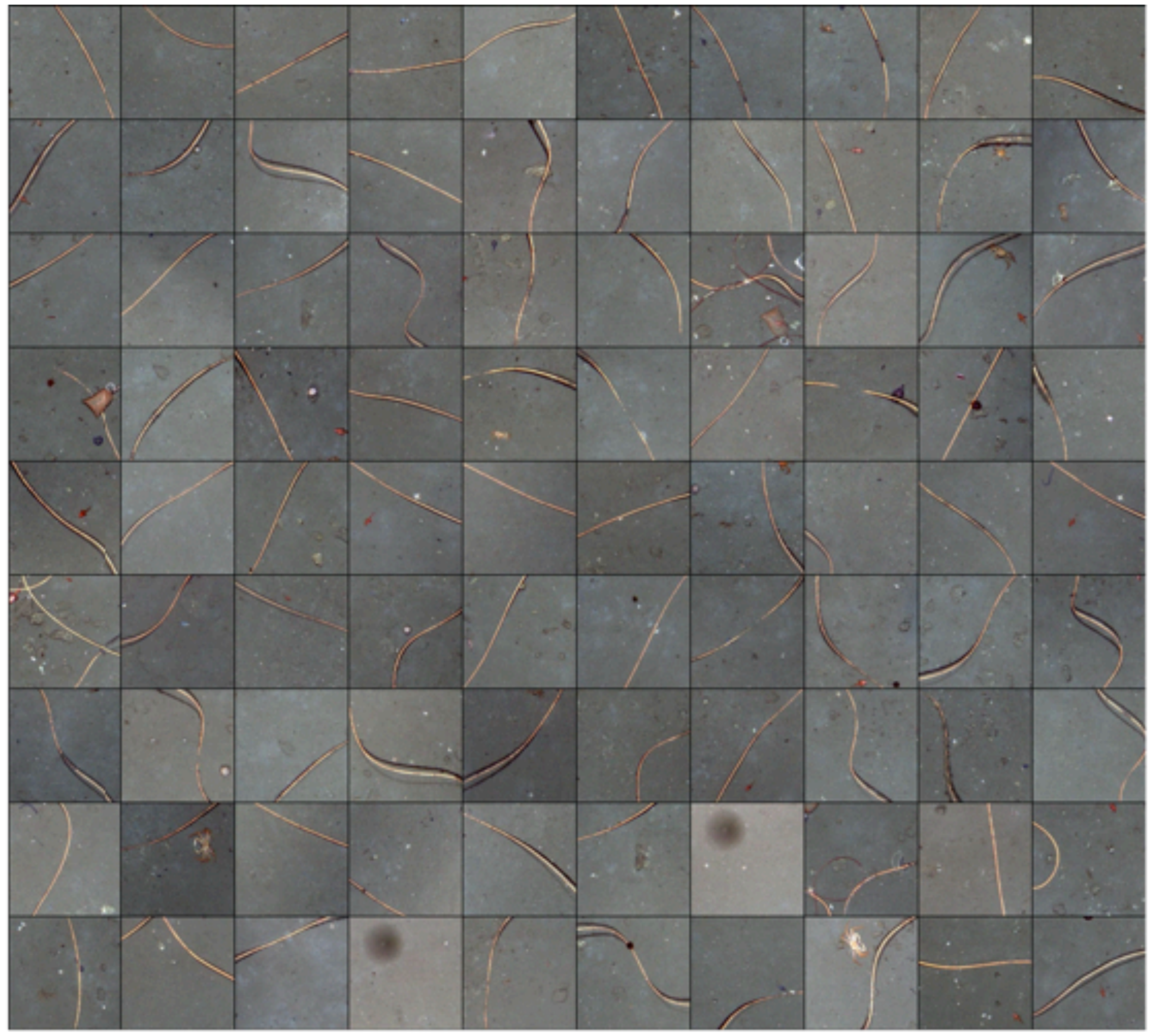

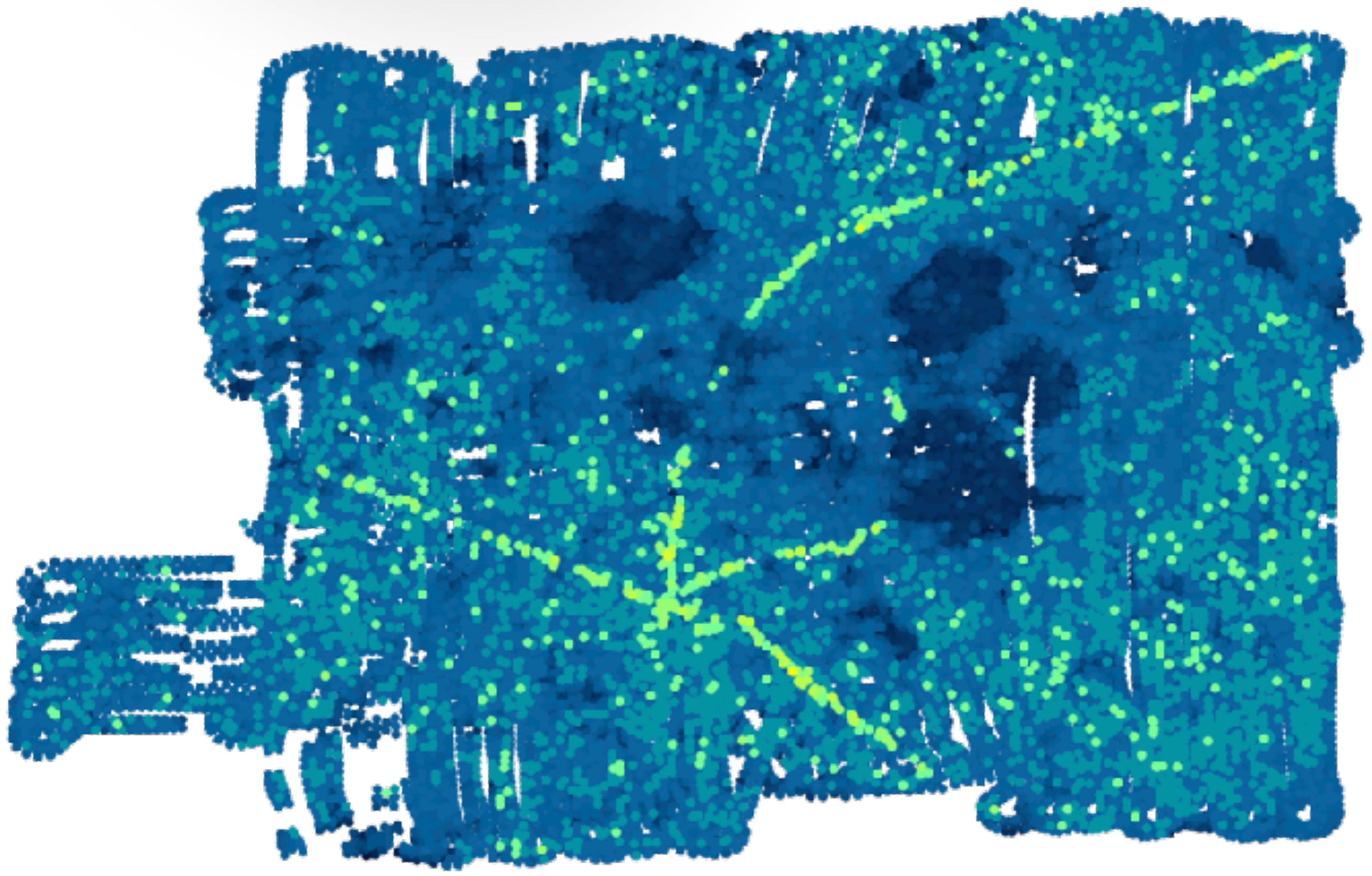

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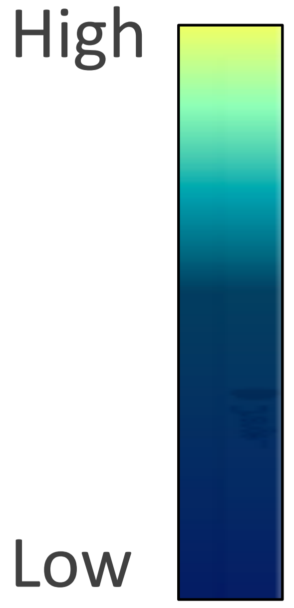

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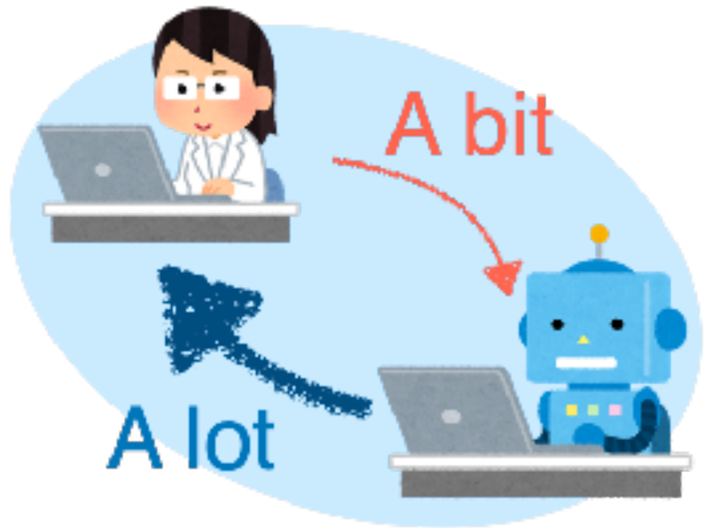
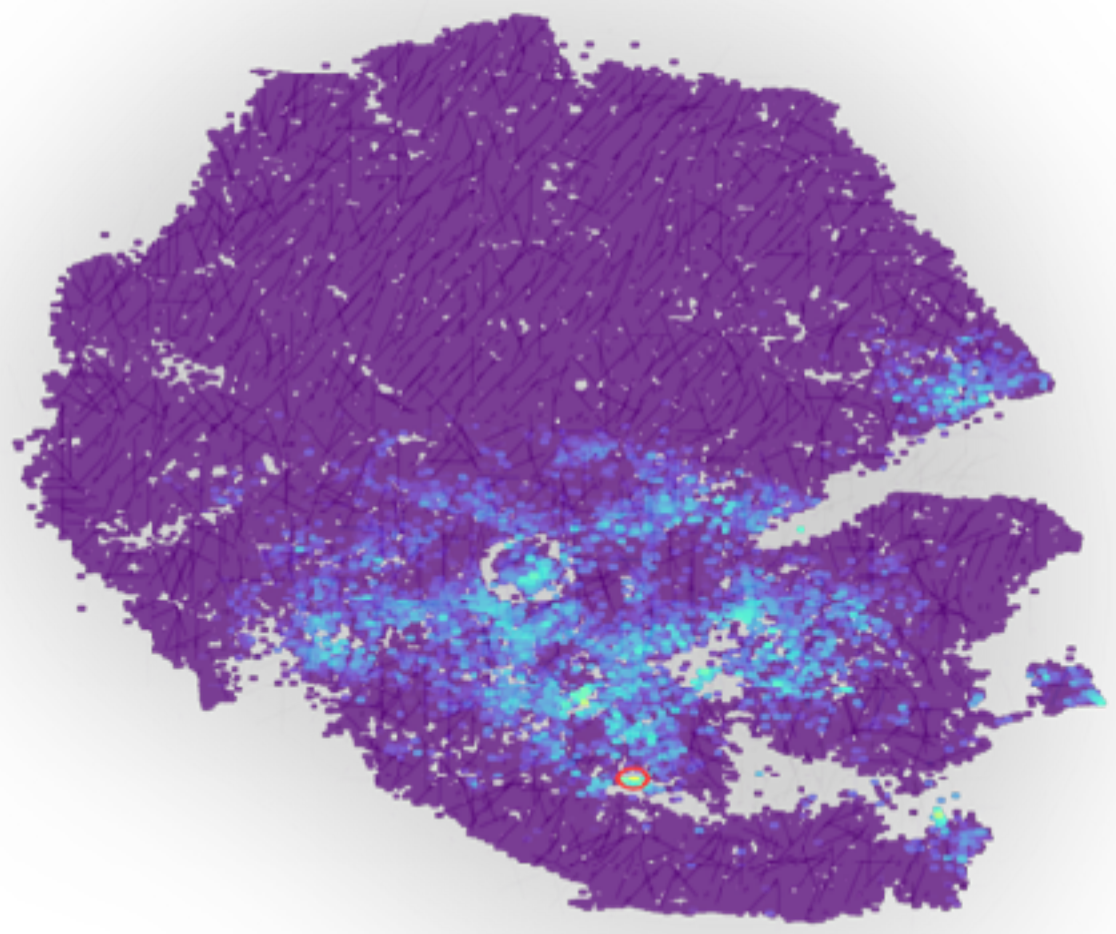
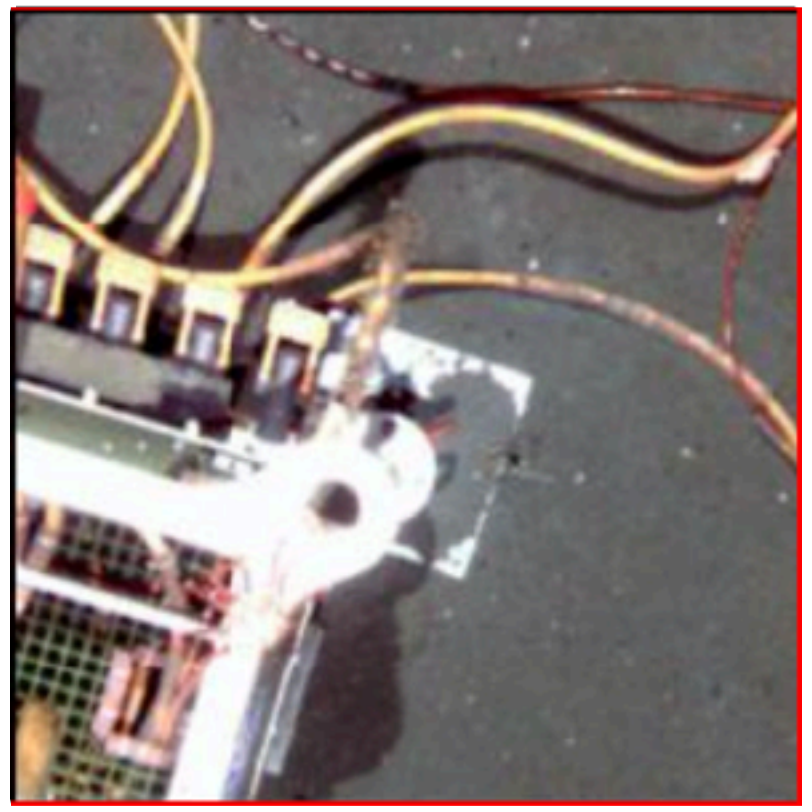


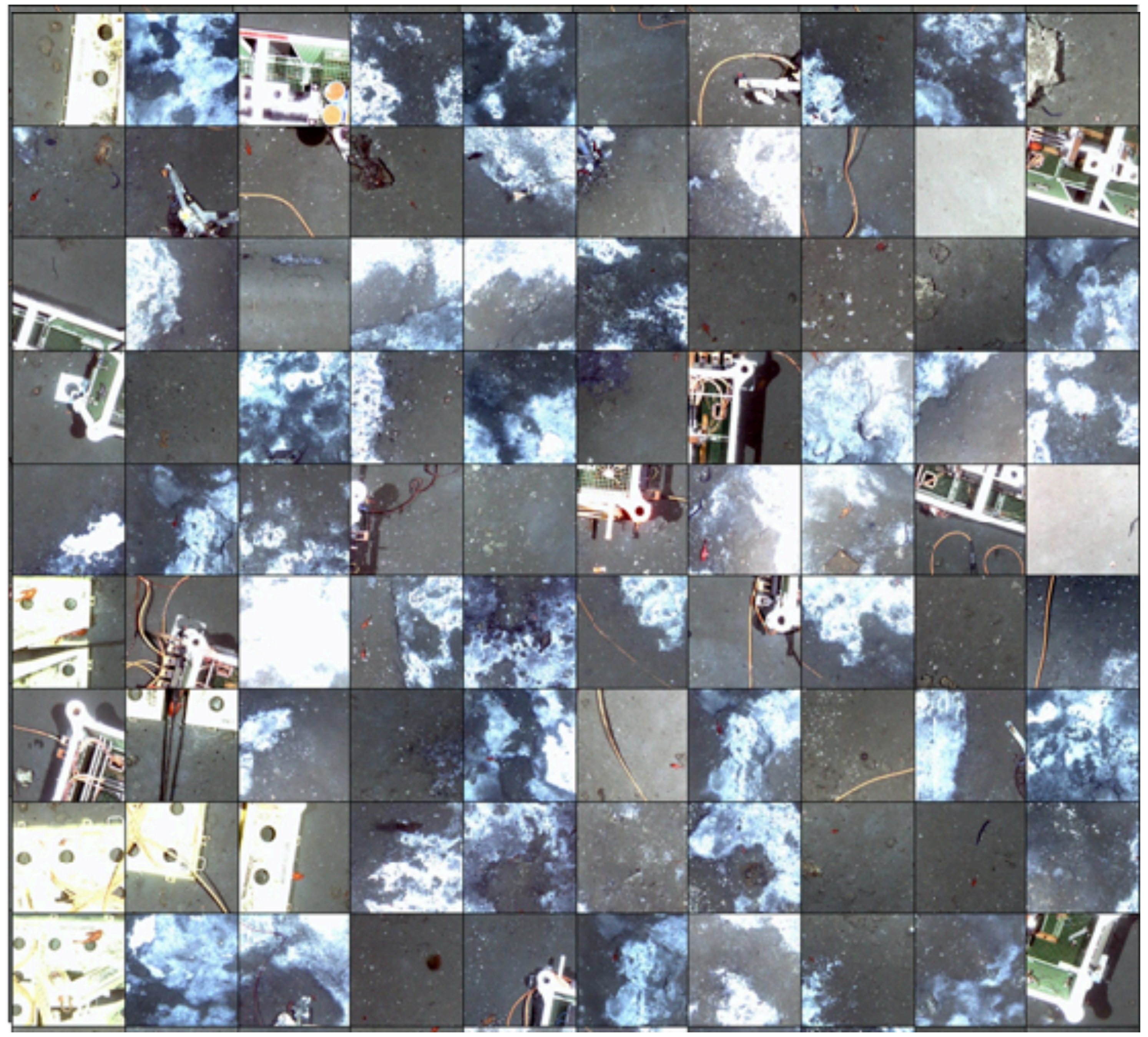


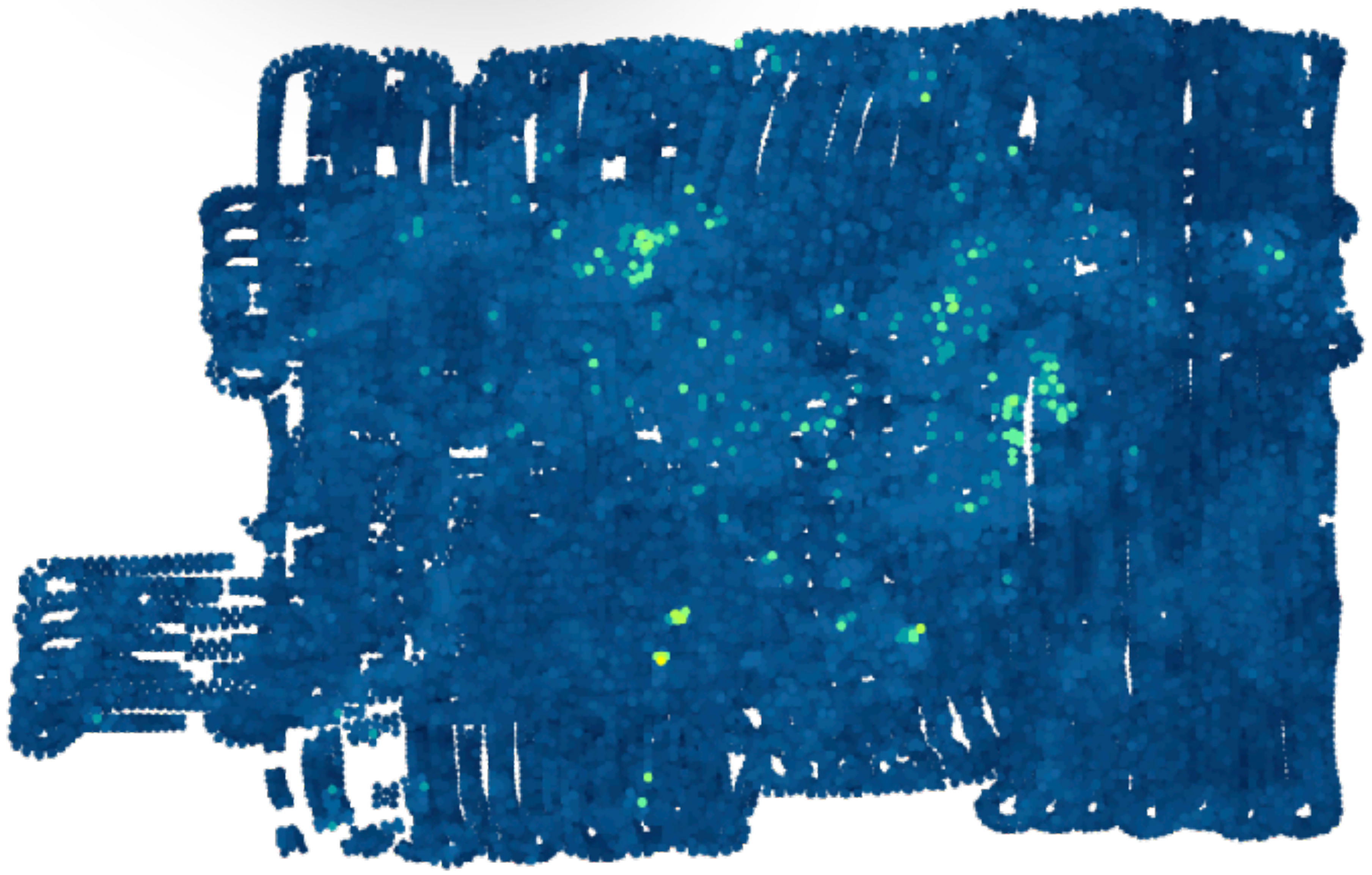
Left: T-SNE Feature space
Right: Query and return
Below: Similarity Map

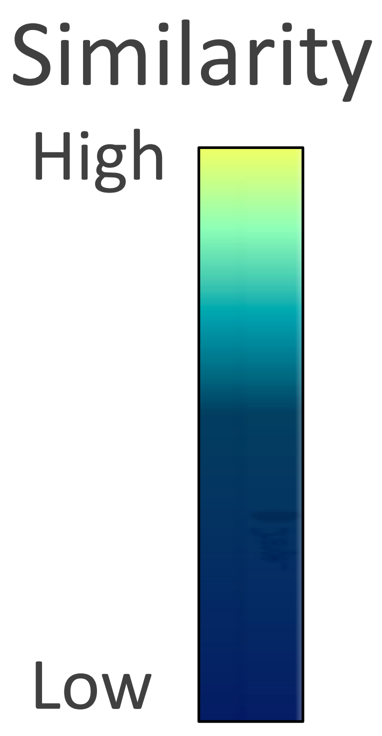
Query image



Similarity ranked return







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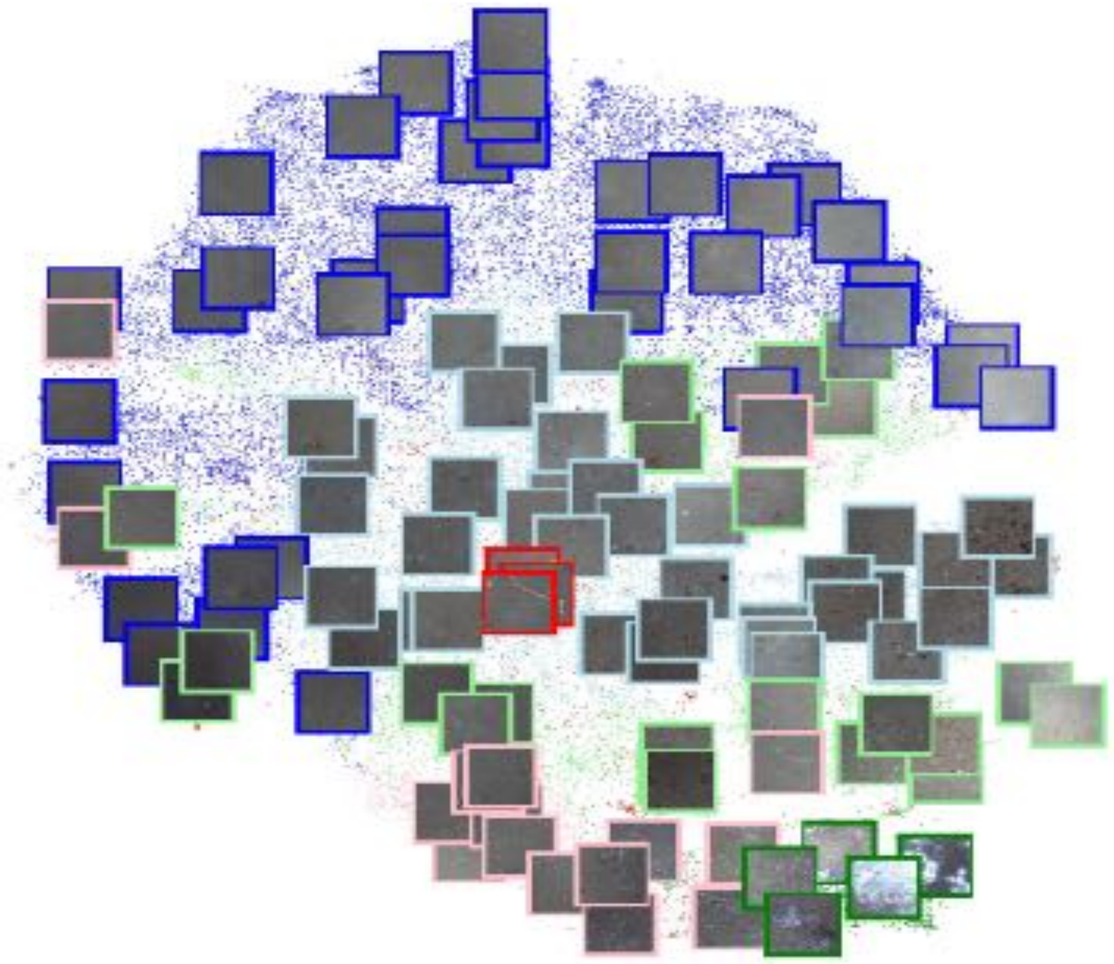
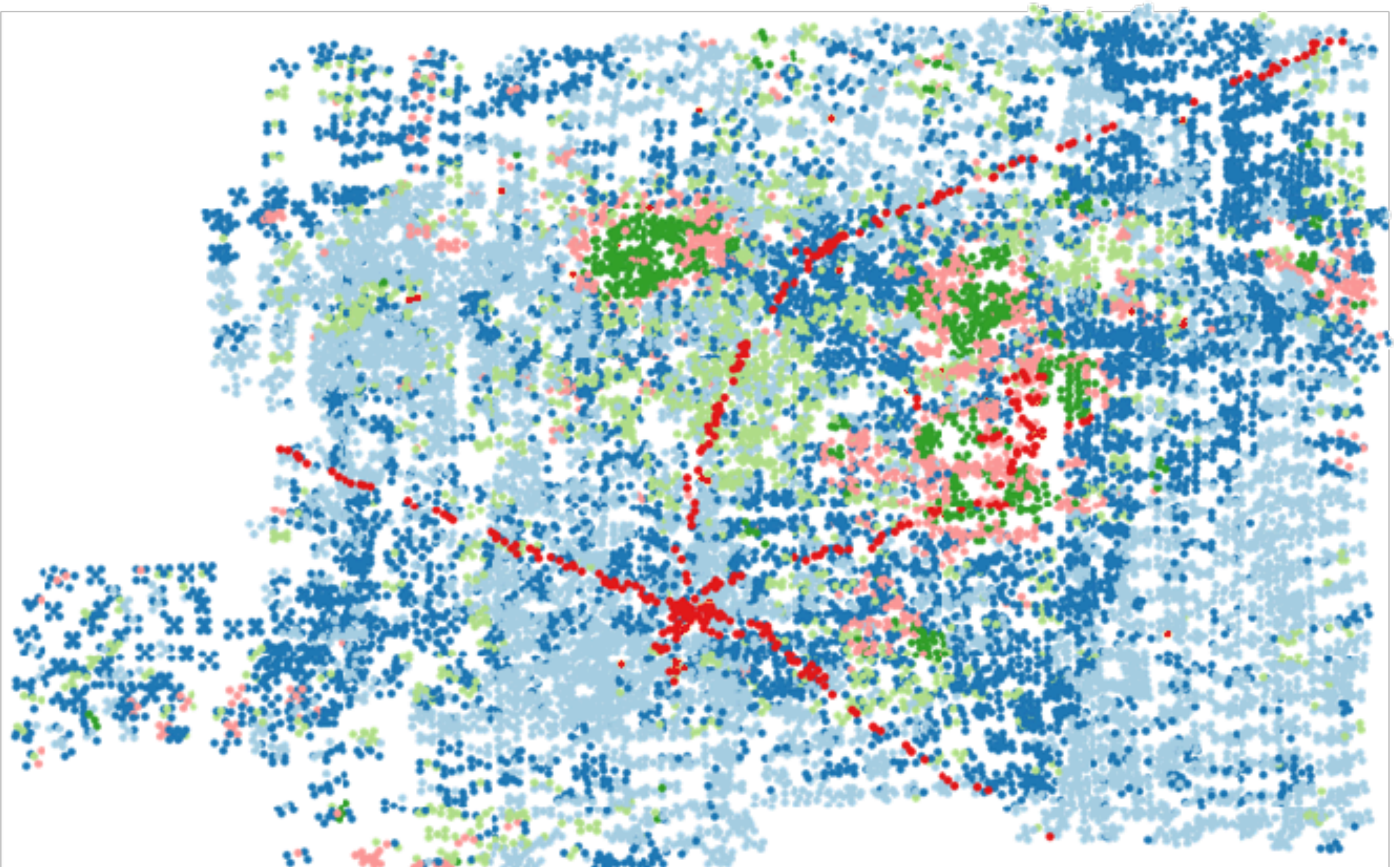
Machine guided human effort

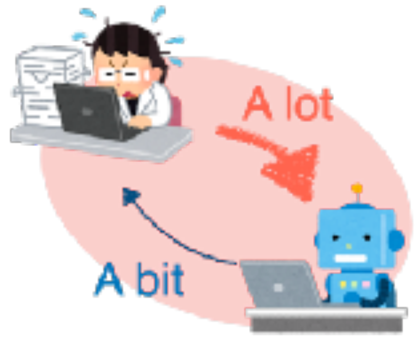
Low-shot with machine prioritized images



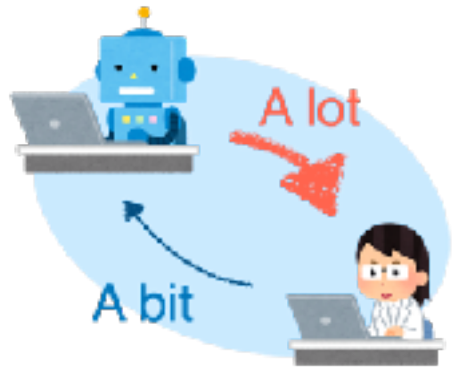
Left: T-SNE prioritisation
Right: Classification
Below: Ground truth



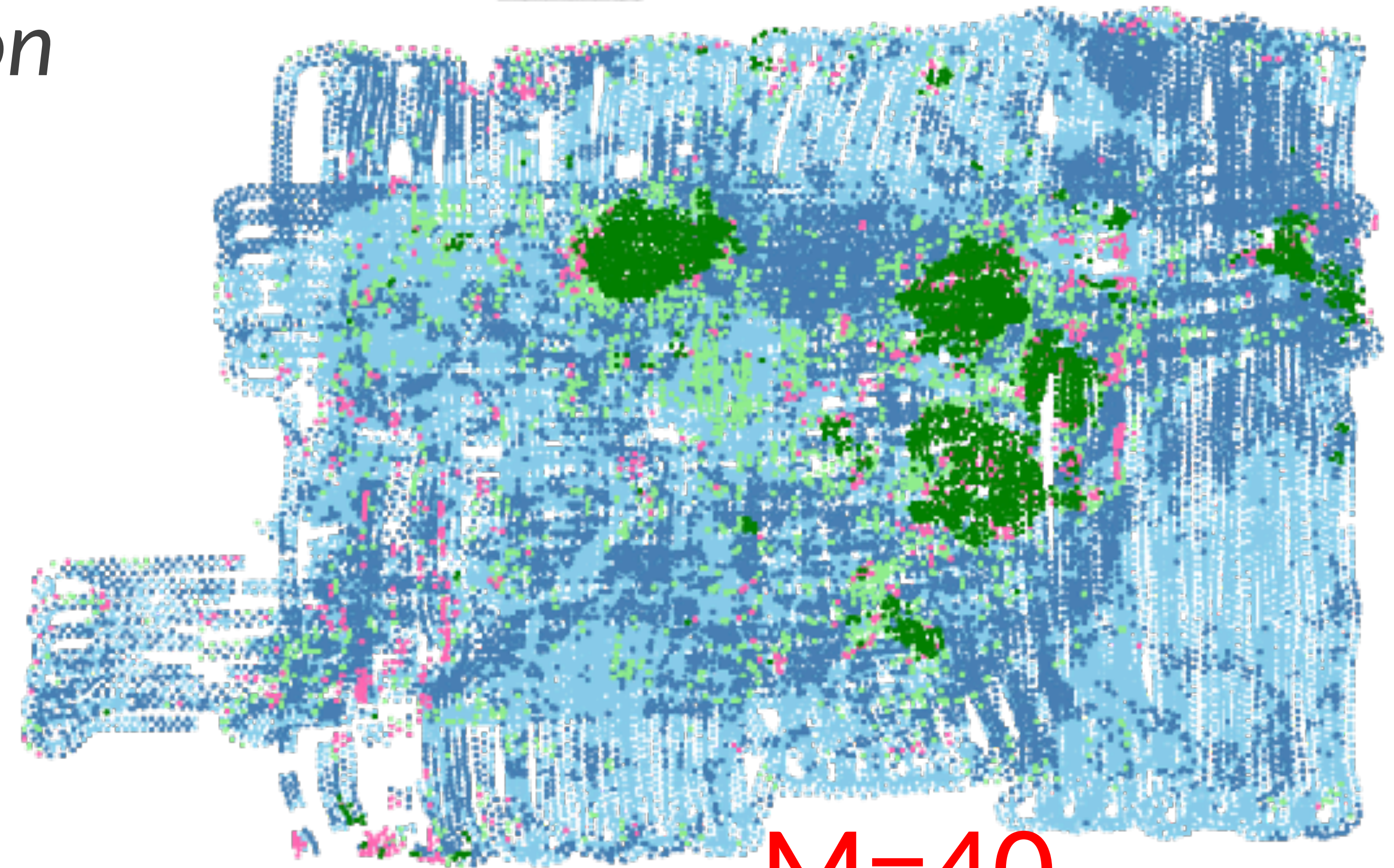
Ground Truth M=18,740



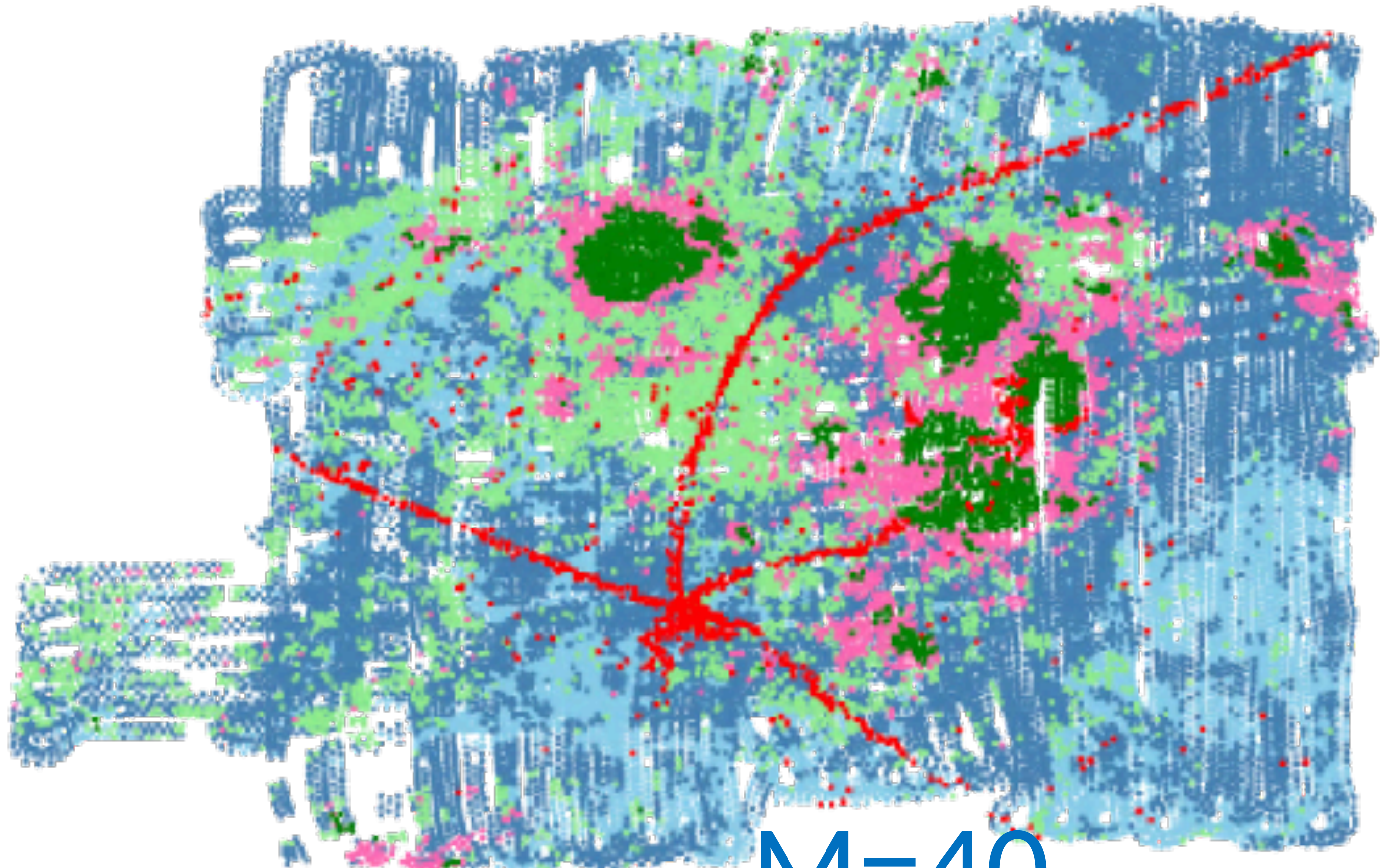
Standard Supervised



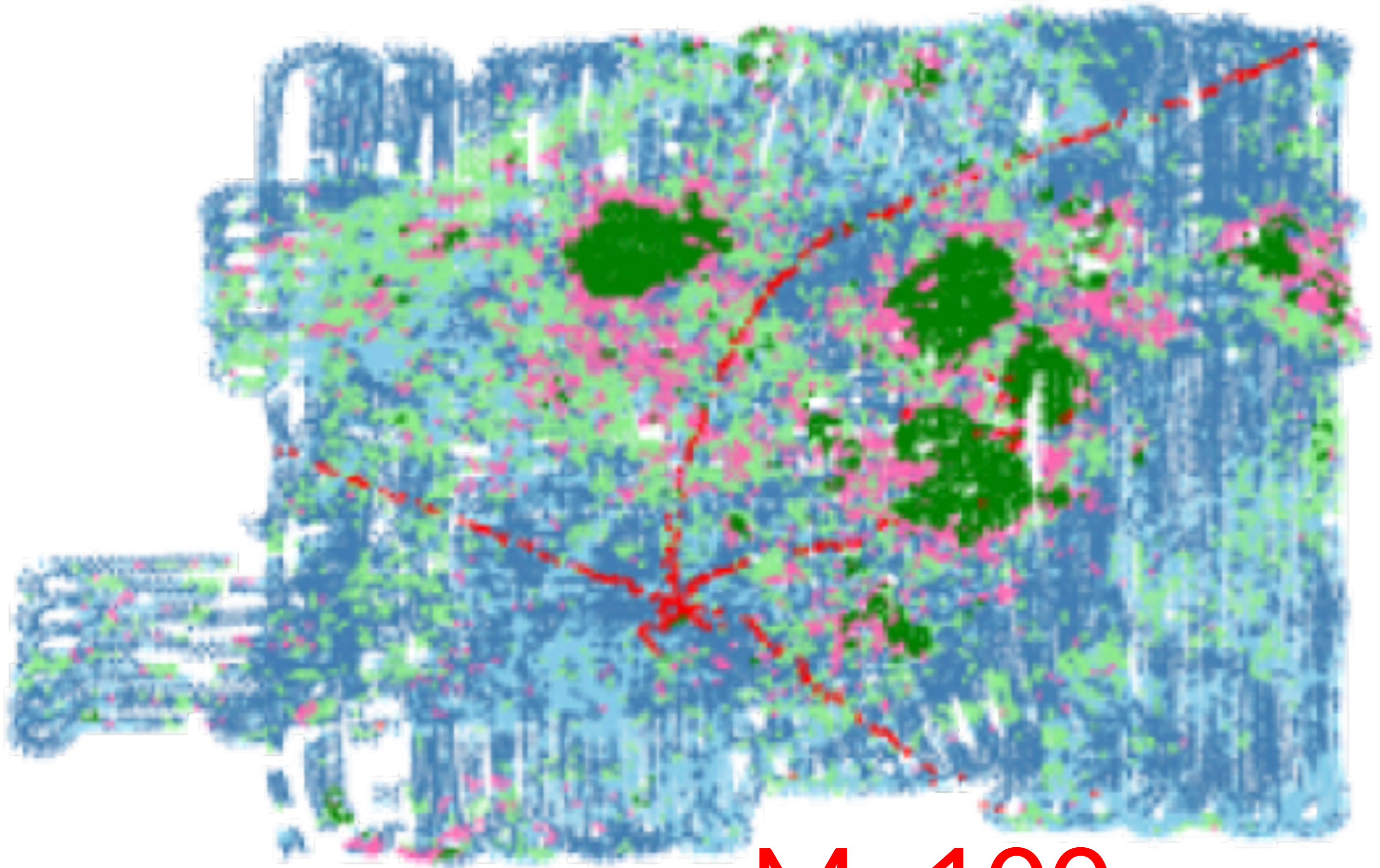
Machine Prioritized



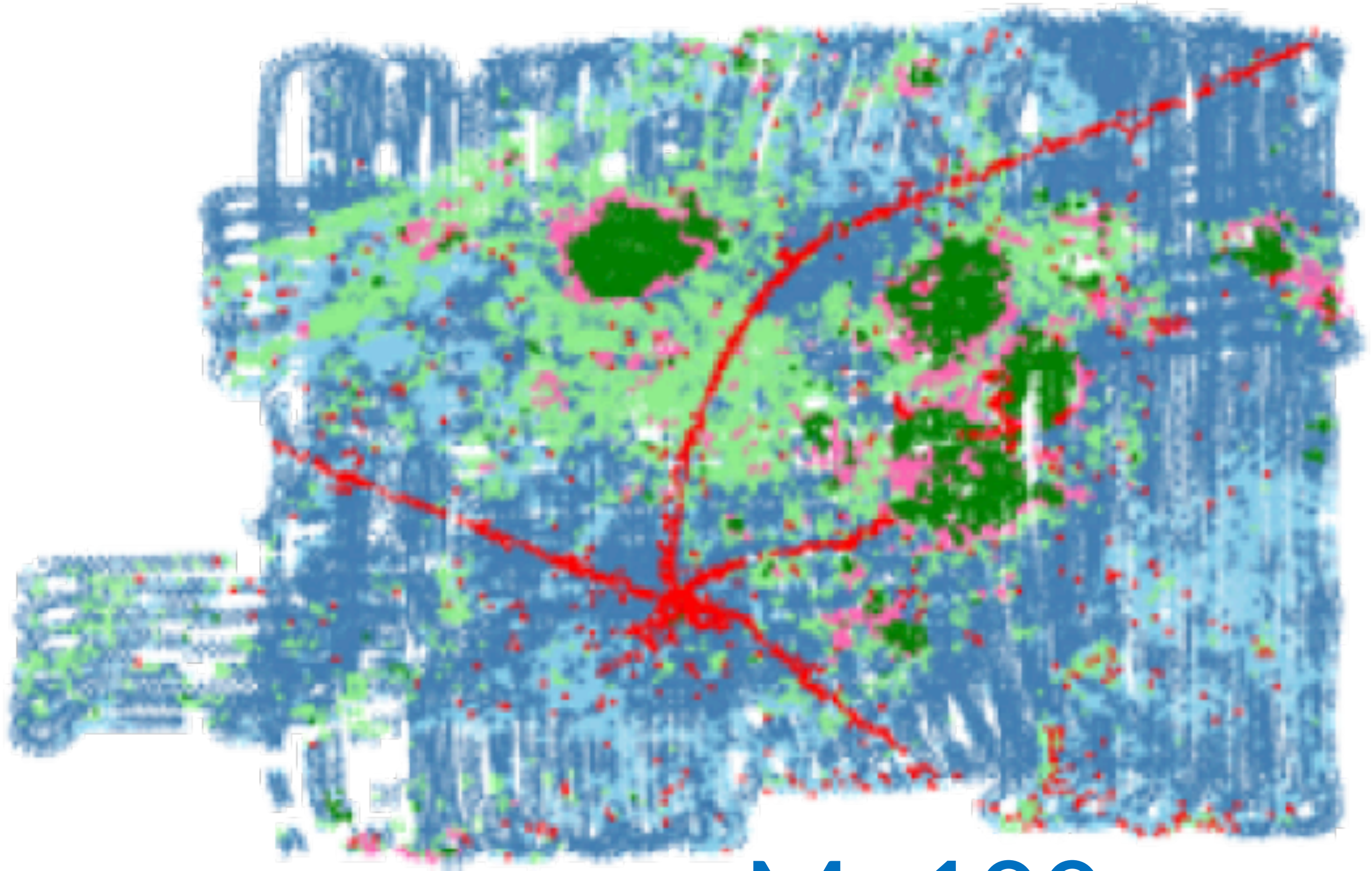
M=40



M=40

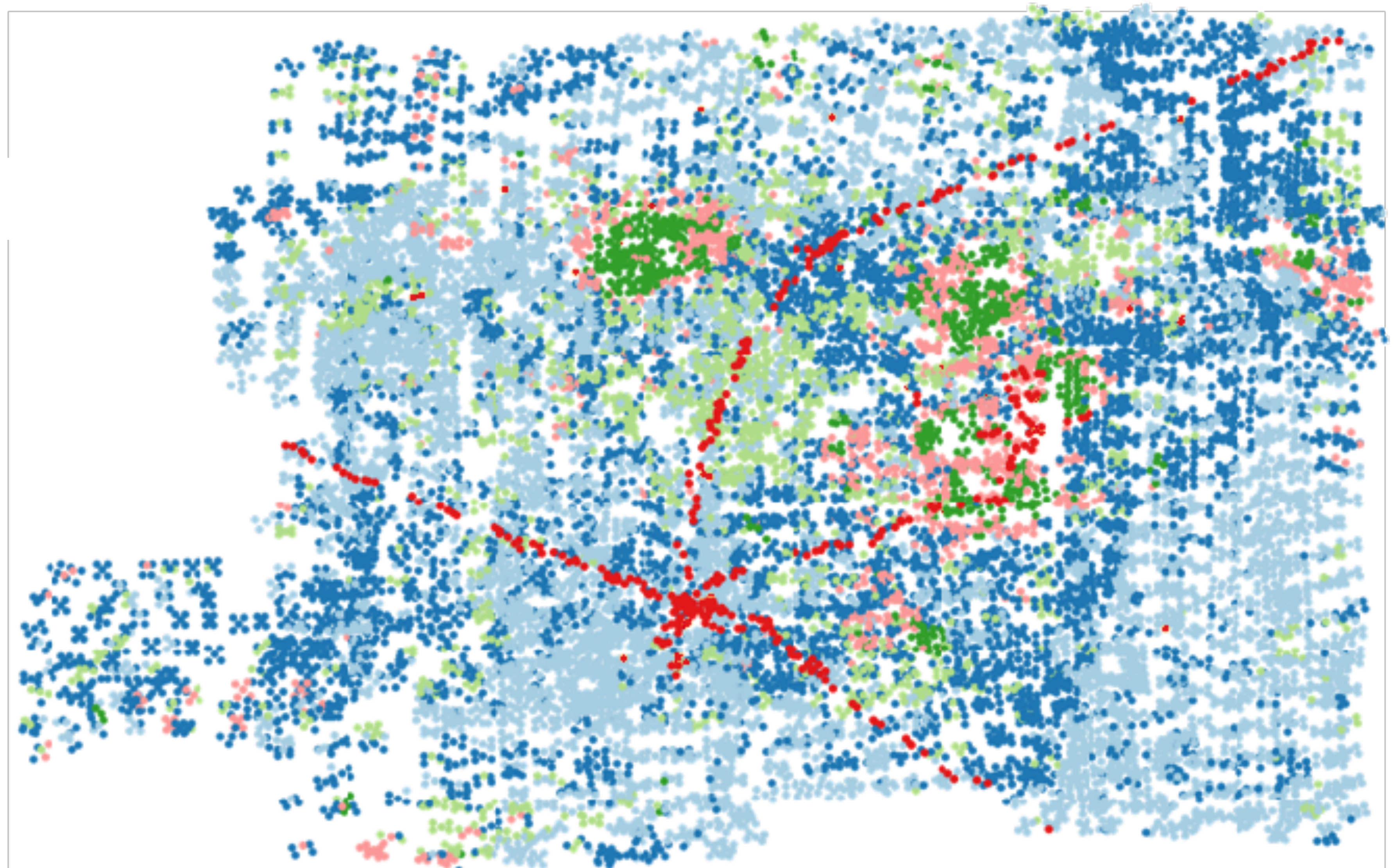


M=100

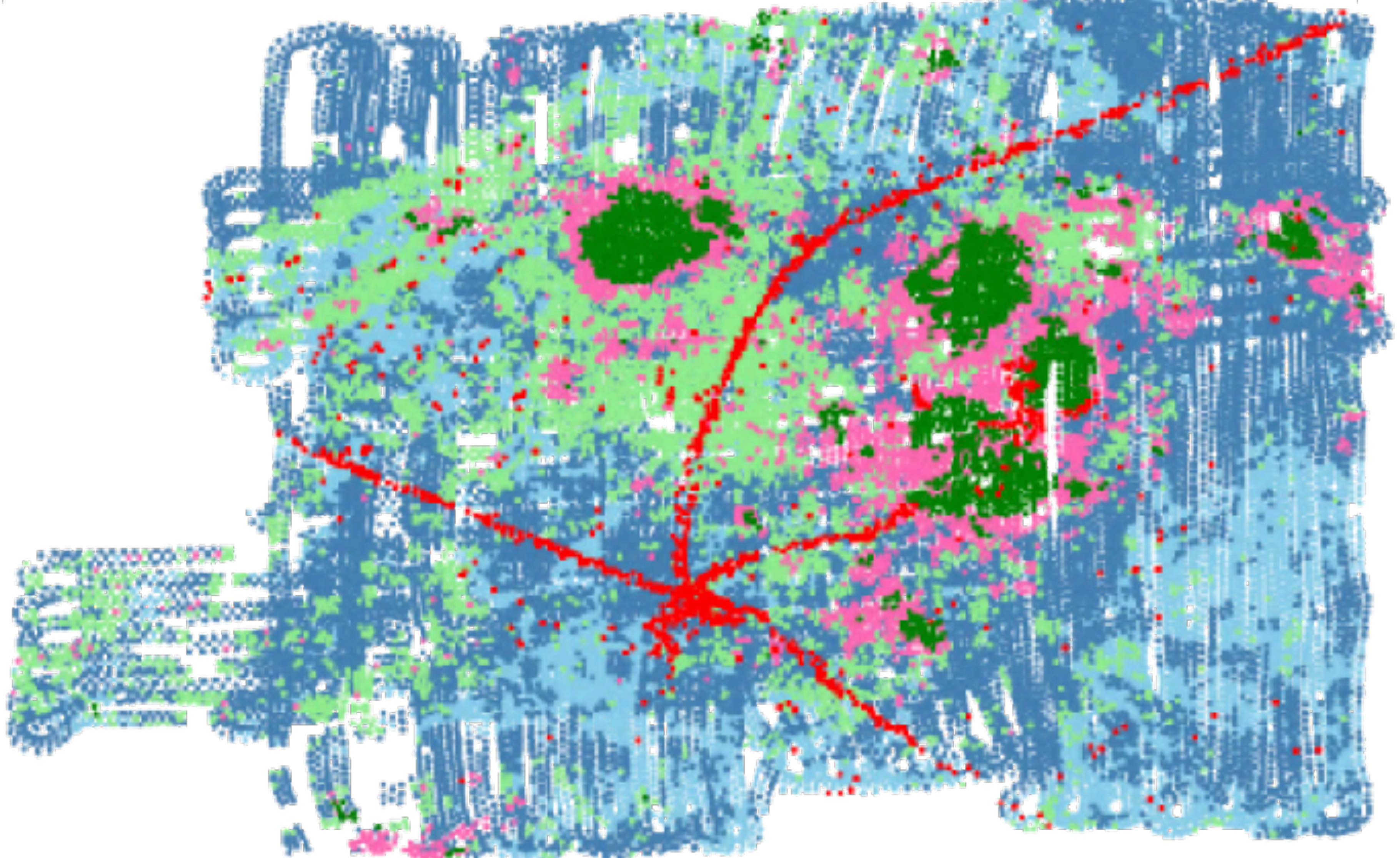


M=100

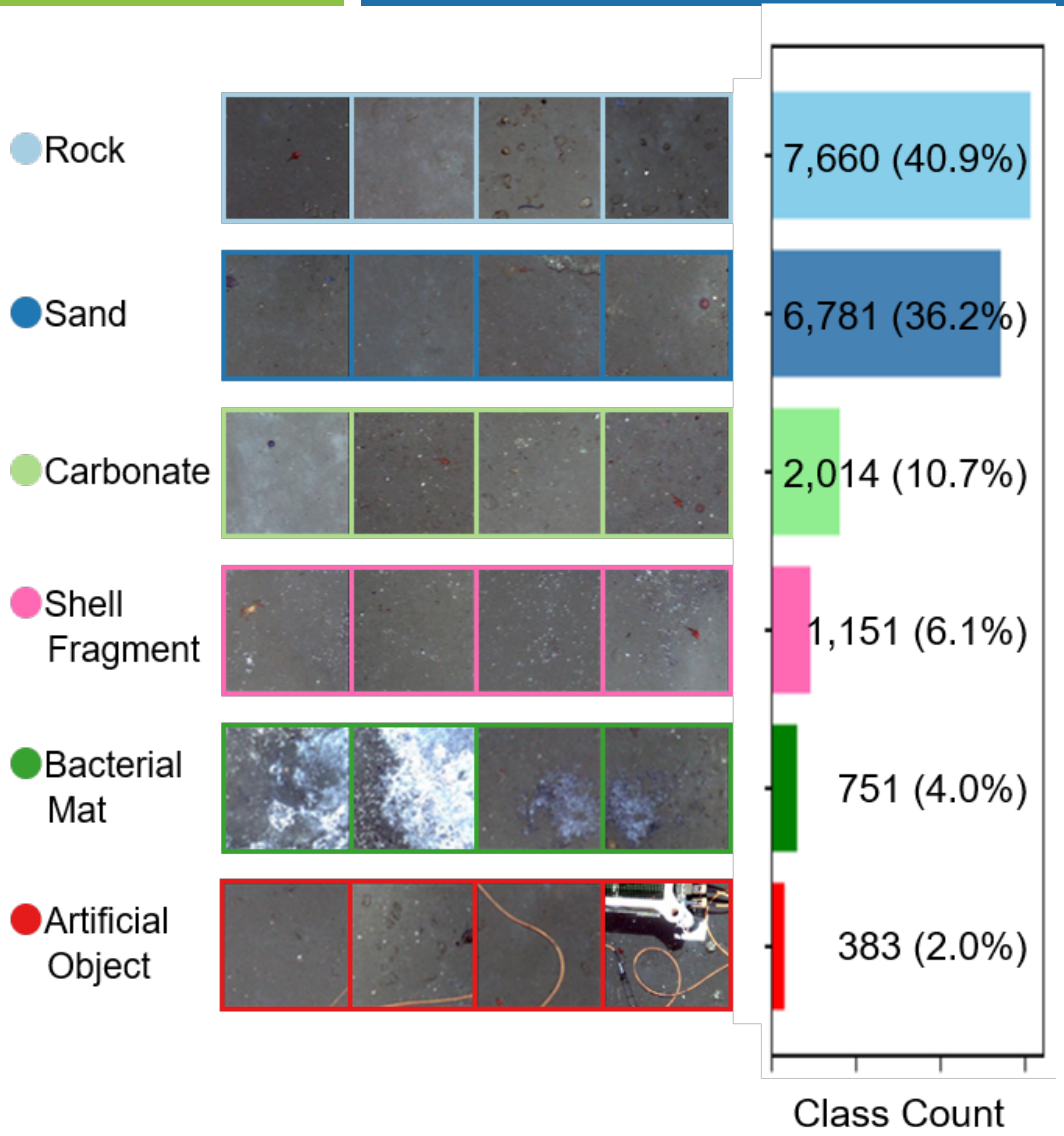
Machine guided human effort



Manual ground truth M=18,740



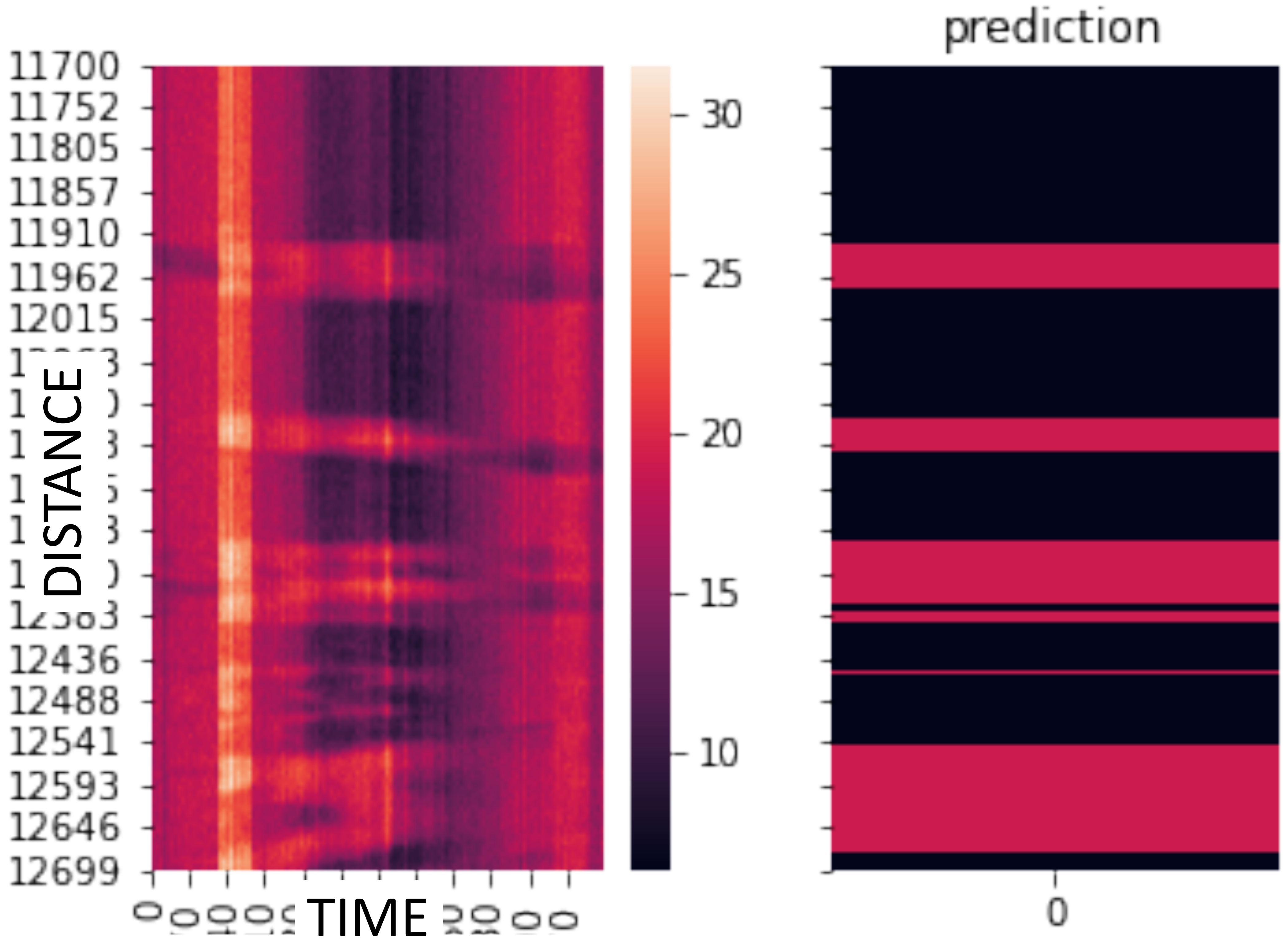
Machine prioritised M=40

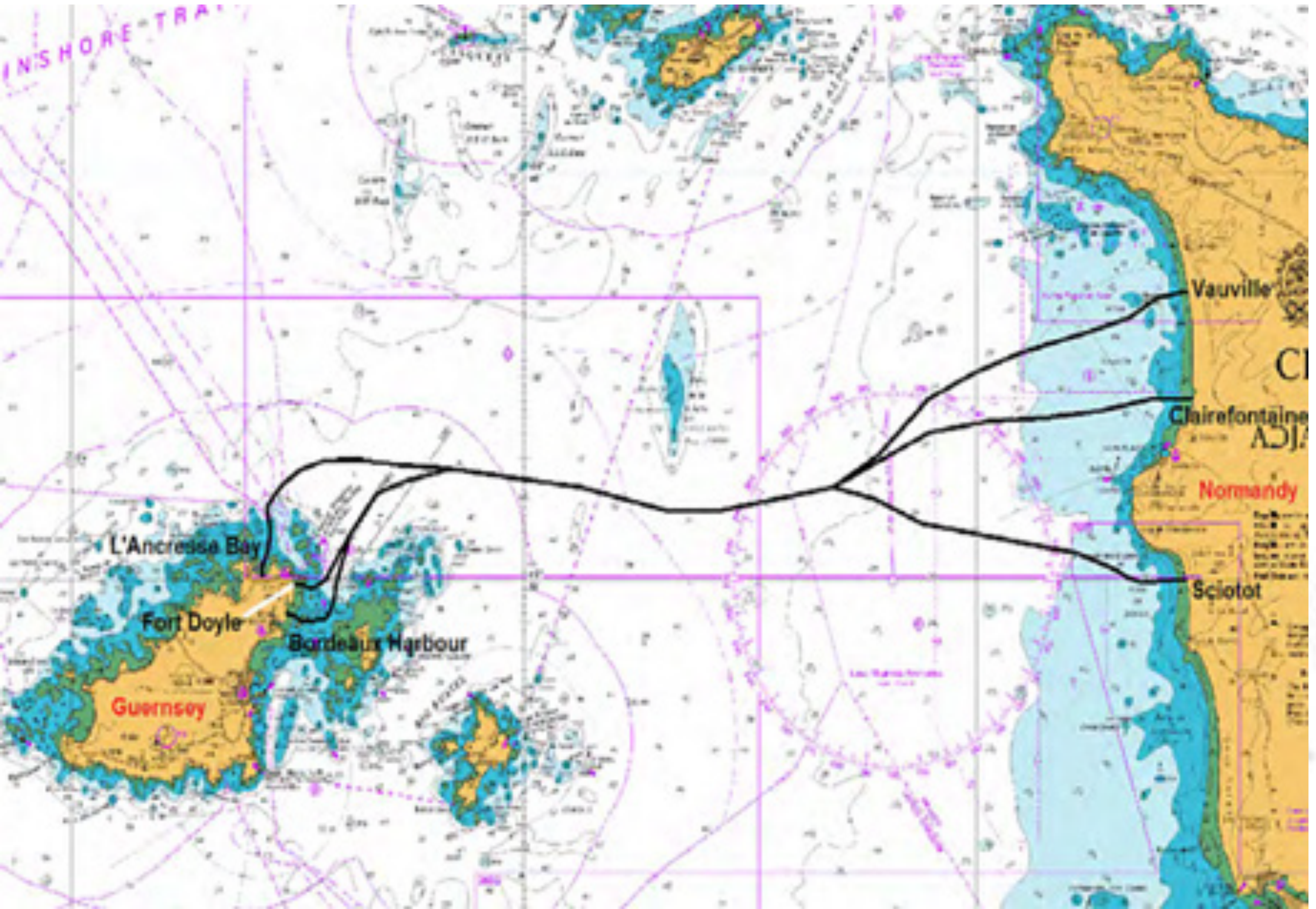


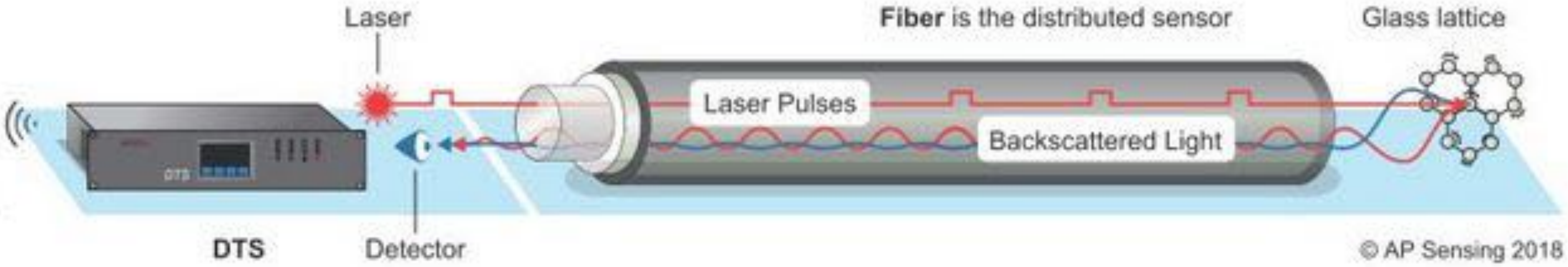
Learning using other types of geospatial data

Other forms of geospatial data

- Not all remote sensing data is “visual”
  - E.g. DTS data from optical cables

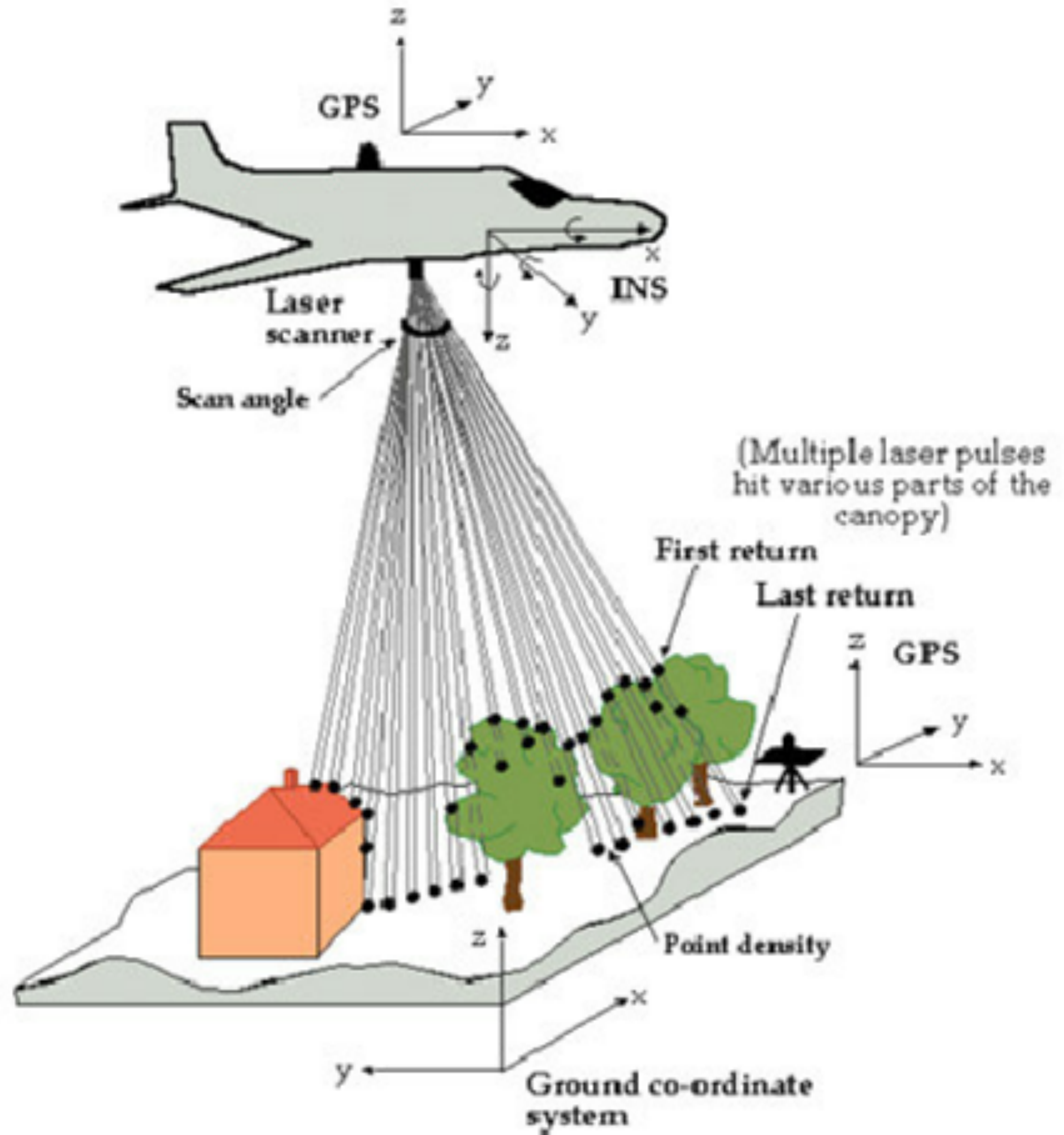


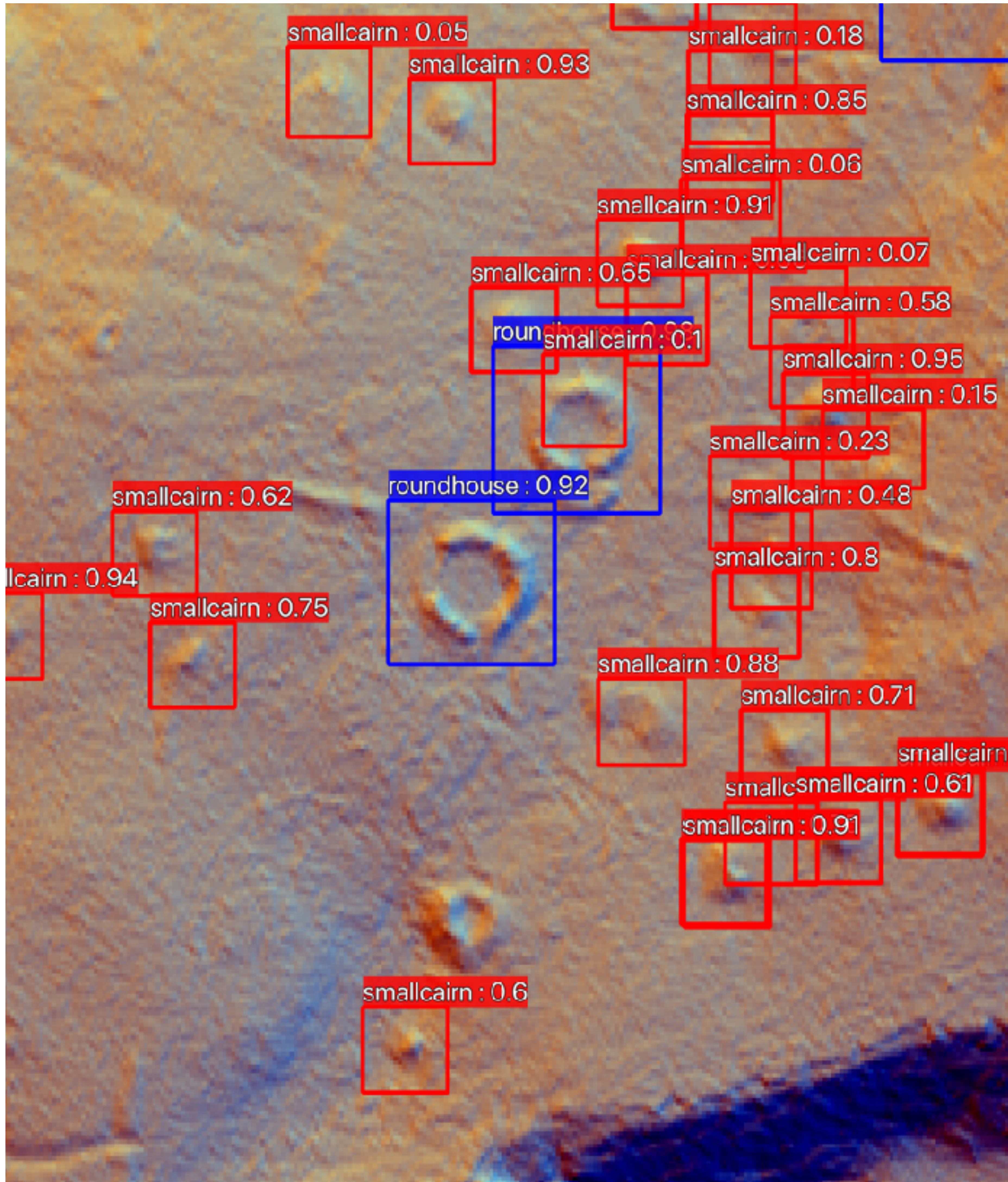




Other forms of geospatial data

- Not all remote sensing data is “visual”
  - E.g. DTS data from optical cables
- Even “visual” data might not be just RGB
  - E.g. Multispectral, Hyperspectral, Phased-array RADAR, LIDAR (DSM, DTM)





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  - Survey data; both qualitative and quantitative
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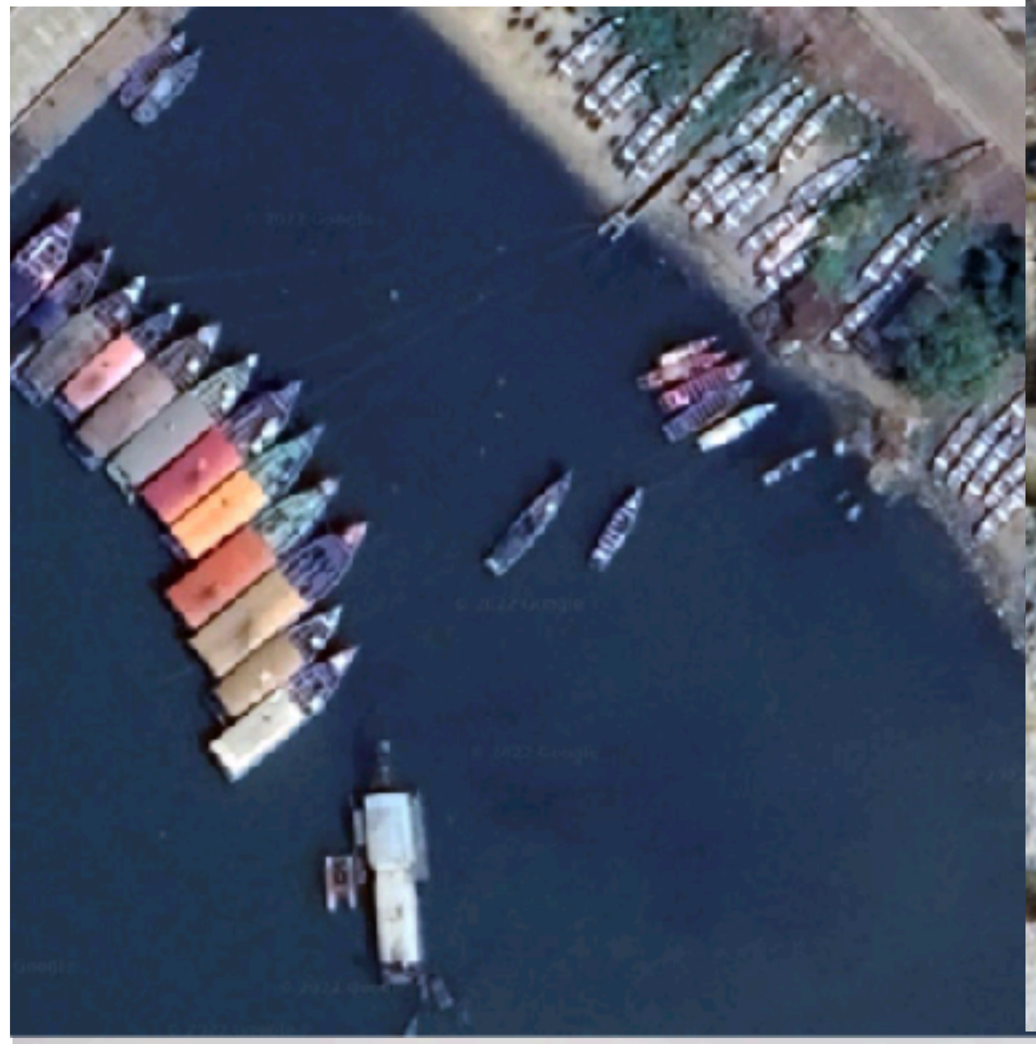

Further technical research challenges

- Not all remote sensing data is “visual”
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Big unsolved problems:

How do build effective learning machines that can leverage all the relevant data for a particular geographical areas? *(multimodal learning)*

Is turning non-image data into image data (where we can) really the best approach?

Take-away messages

- Machine learning and AI can help you solve problems and answer questions
  - But machine learning is not magic
    - It can learn the wrong thing, and it can be difficult to understand this
    - You might have to search for a model that works well on your problem