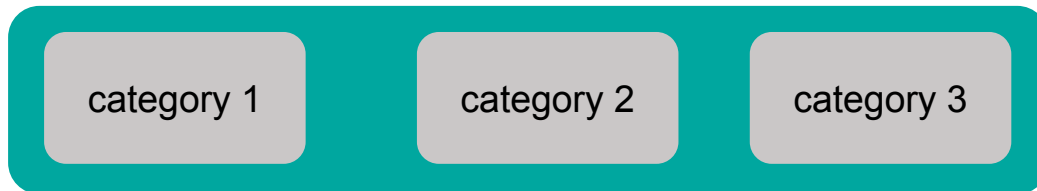


Meta-learning data-efficient Machine Learning Models for Diverse Earth Observation Problems

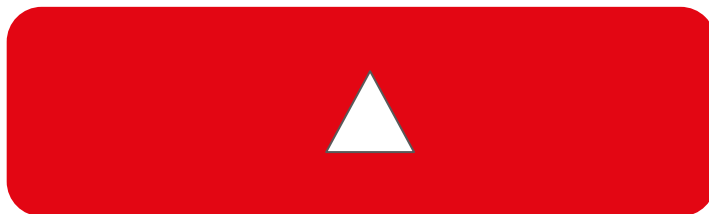
Marc Russwurm

postdoctoral researcher
EPFL-ECEO Laboratory
Valais, Switzerland

Category: One, two, oder three?



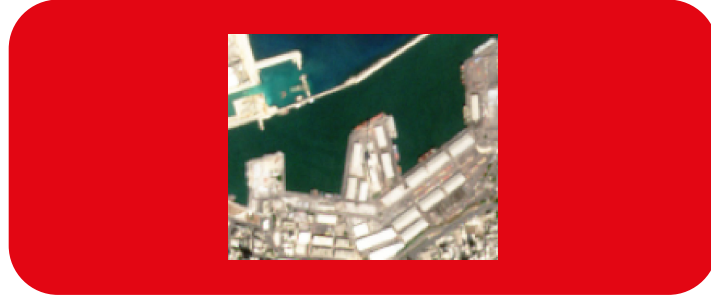
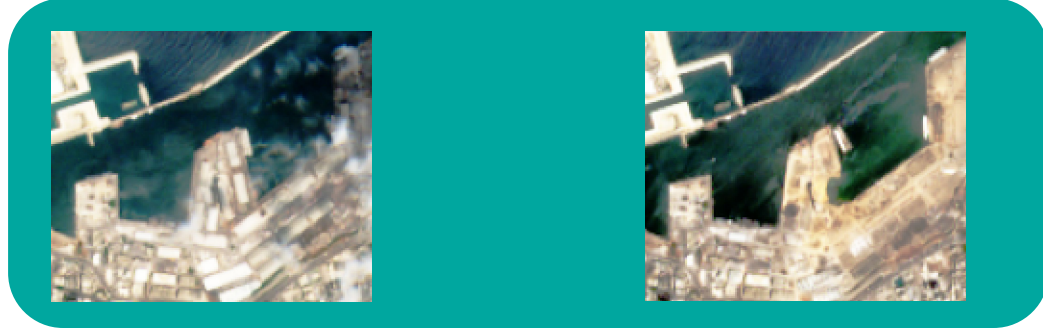
Triangle, square, or circle



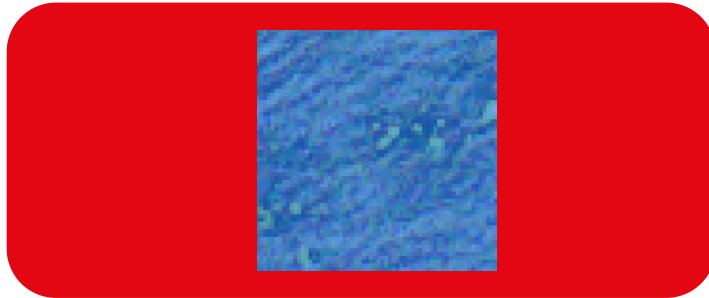
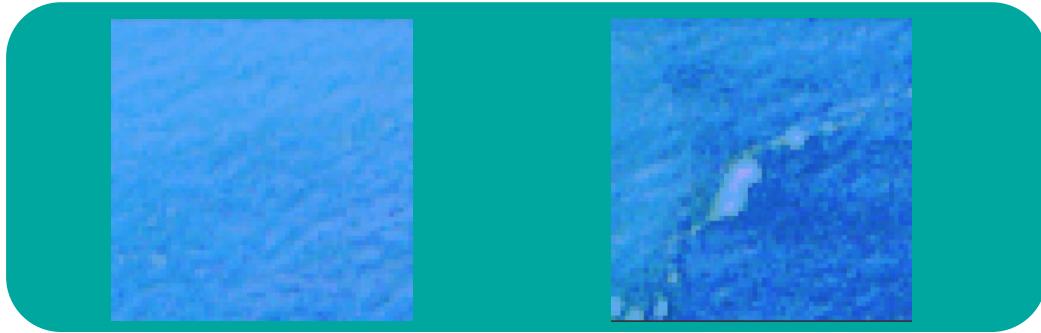
Savanna, urban, or water?



Before or after?



Water or marine debris?



What is this? ...tasks!

within a single task:

- we learn from a **training set**
- to associate samples on a **test set**

We (humans) are really good at solving tasks with only few training images

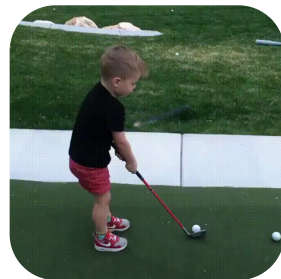
task:



Why is it so easy for us to solve tasks?

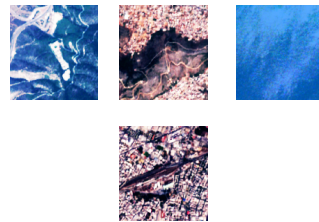
■ ECMWF ESA workshop on machine learning for earth observation and prediction

... because our life consists of solving tasks!



a tiny bit more difficult

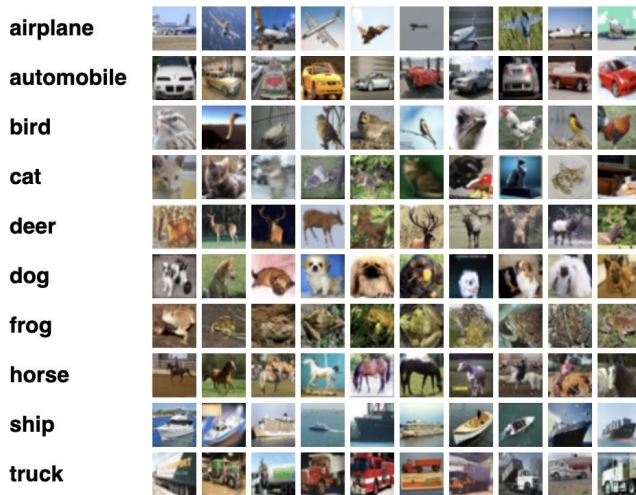
baby easy!



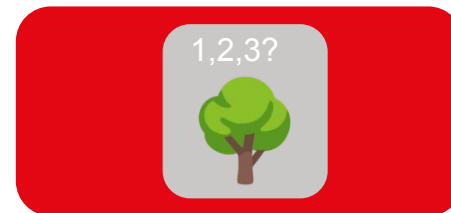
Deep learning needs a lot of labelled data to solve a single task

CIFAR-10: 6000
examples per
class

CIFAR-100: 600
examples per
class



600-6000 training examples per category



... because we train deep learning models on **one** training dataset

The training dataset is a **window** through which the learner gets partial information about the world

[Shai Ben-David and Shai Shalev-Shwartz, 2014]

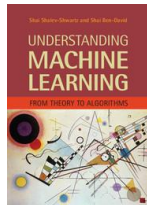


Photo by [Nicolas Solerieu](#) on [Unsplash](#)

To improve machine learning models

Strategy 1:

We can increase the size of our datasets

large “foundation” models



photo by [Forbes Magazine](#)

Strategy 2:

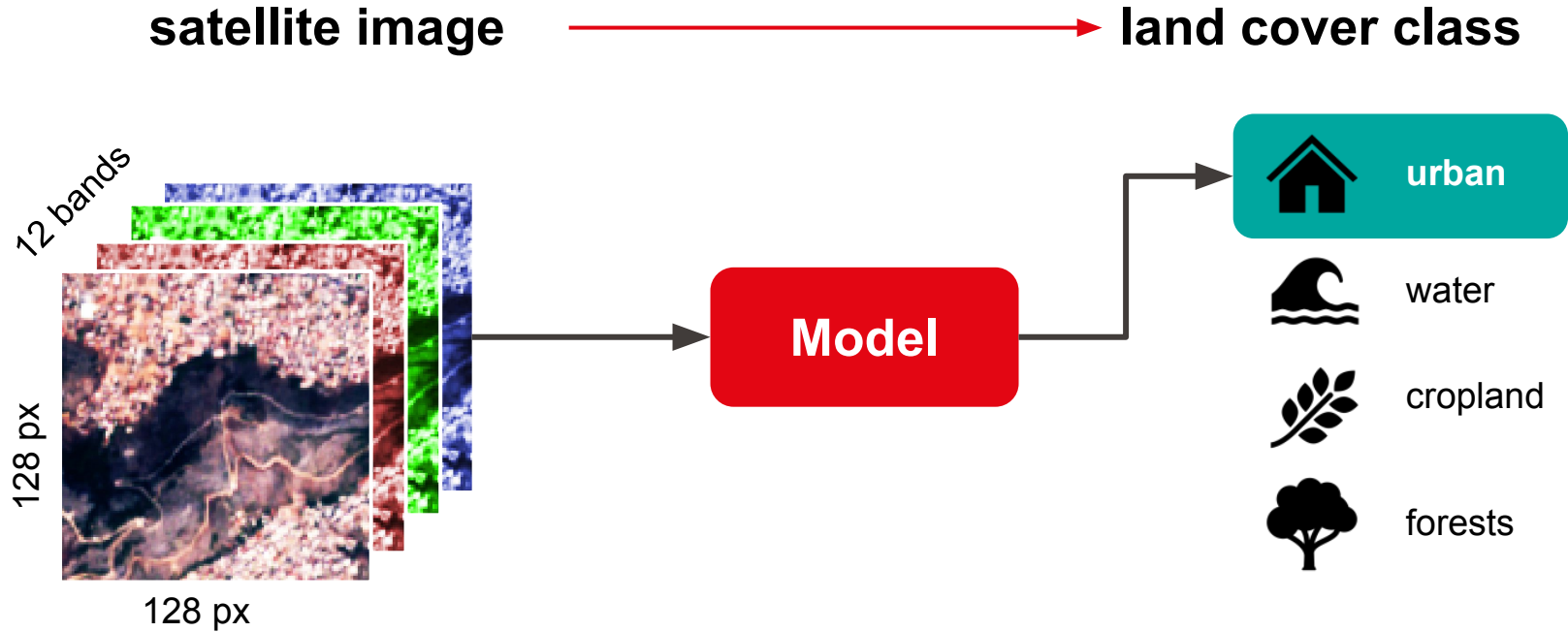
We can include many different datasets

many small adaptive models



photo by u/logatwork posted in /r/bizarrebuidings

Concrete Example: Land Cover Classification

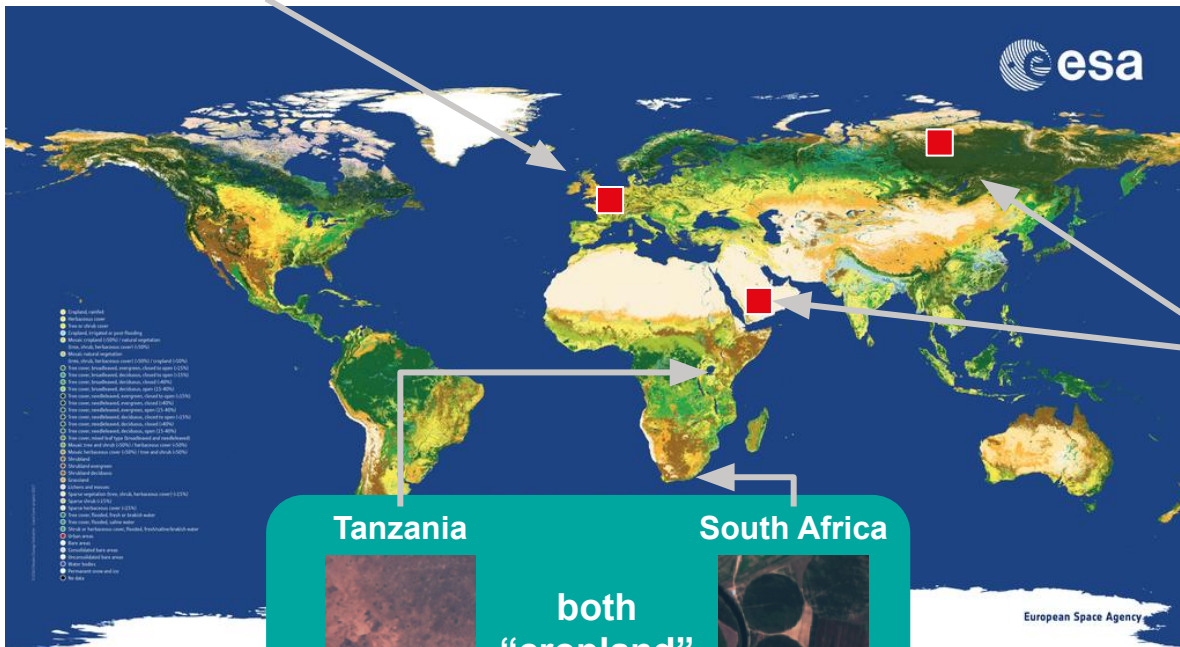


A Global Land Cover Model



are used to quantify urbanization and deforestations

often coarse on local scales



a fixed set of classes

some never appear together like snow/ice and desert

Tanzania South Africa
both "cropland"



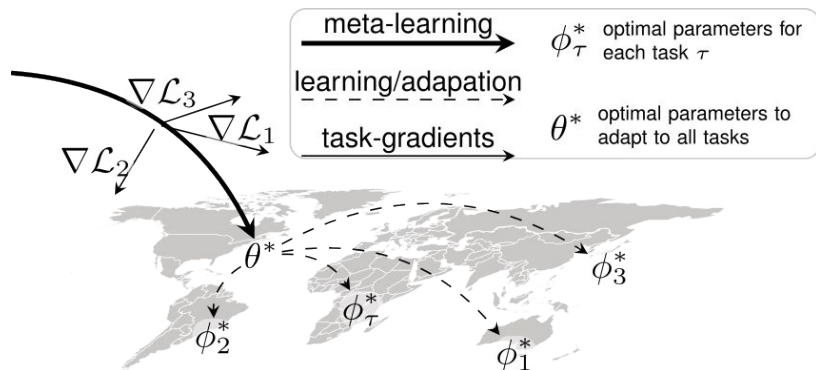
concept

meta-learning
a global adaptive model

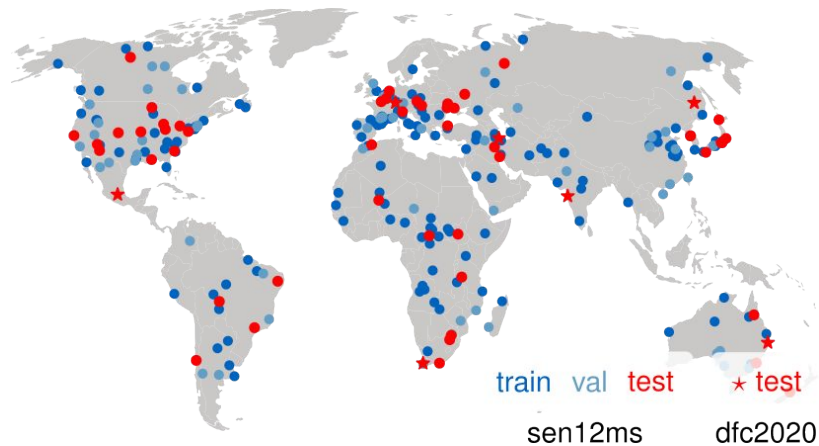
fine-tune

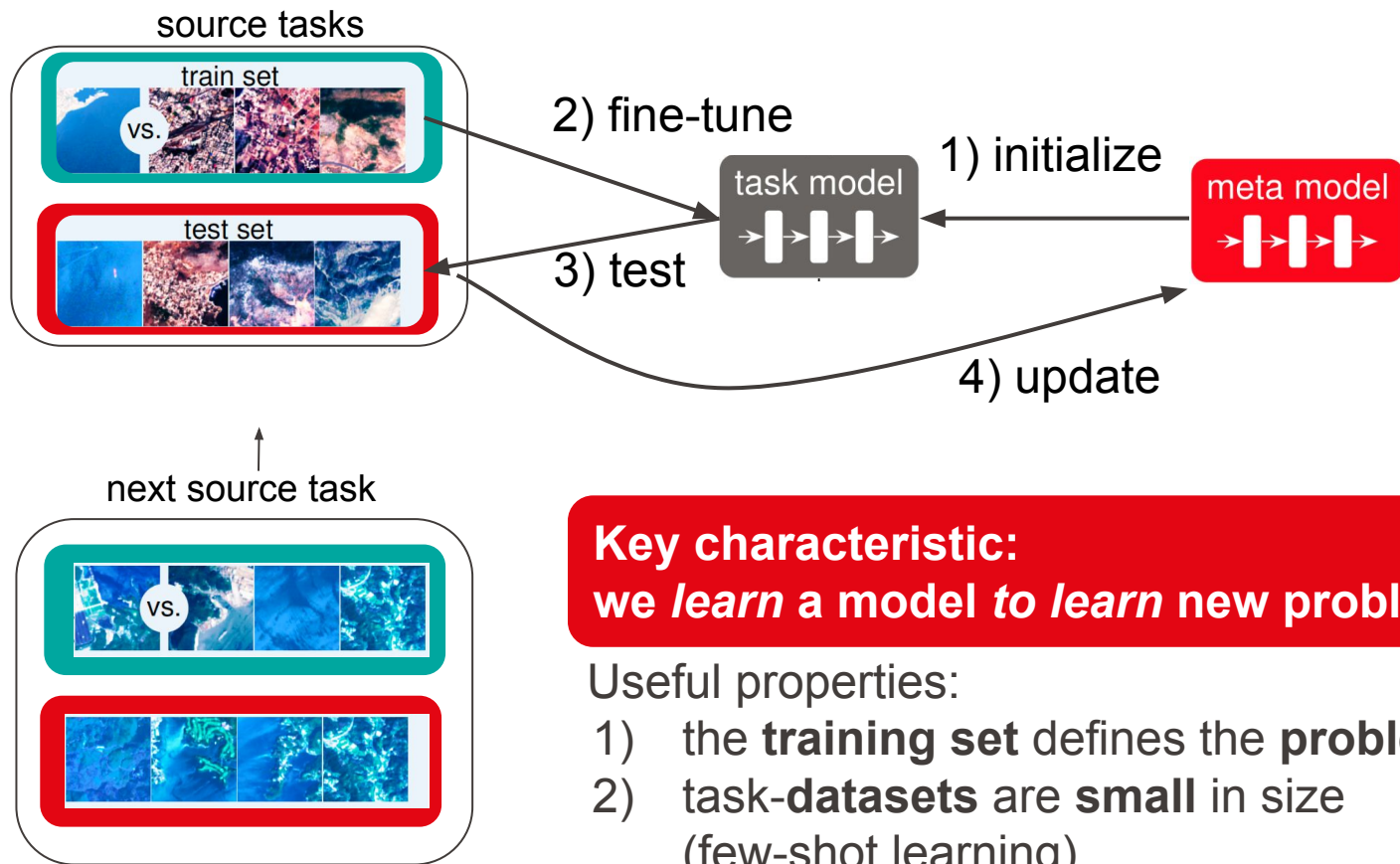
regional model
with few annotated samples

Model-agnostic meta-learning (Finn et al., 2017) naturally allows for different data distributions between tasks



a dataset of tasks



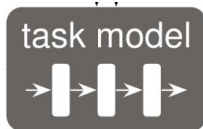


Key characteristic:
we learn a model to learn new problems

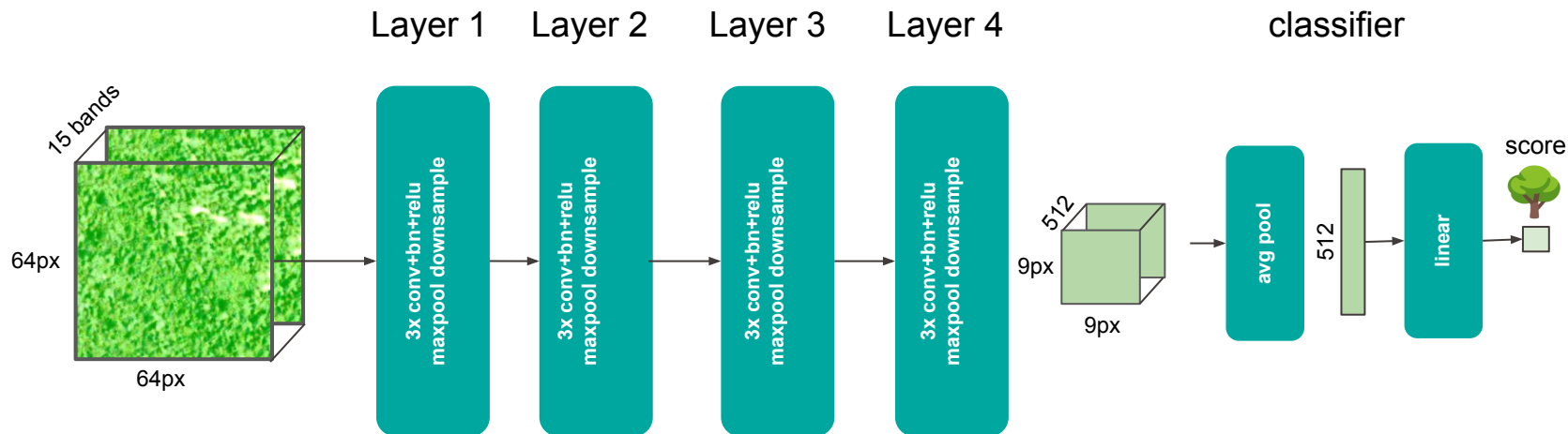
Useful properties:

- 1) the **training set** defines the **problem**
- 2) **task-datasets** are **small** in size (few-shot learning)

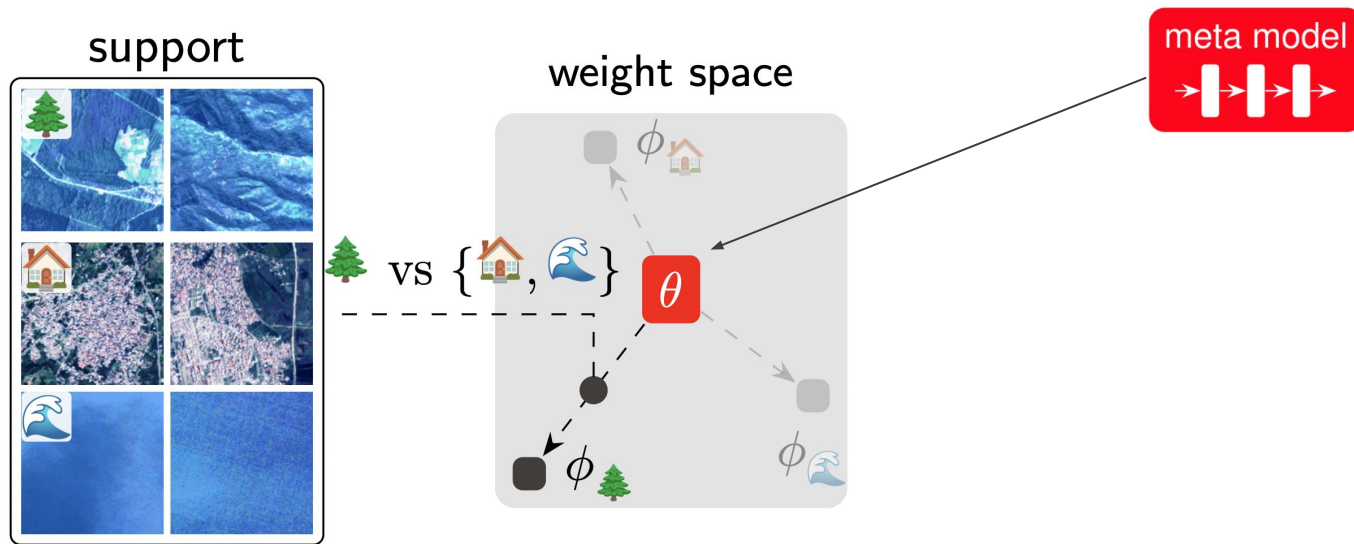
ResNet-12 one-versus-all classifier



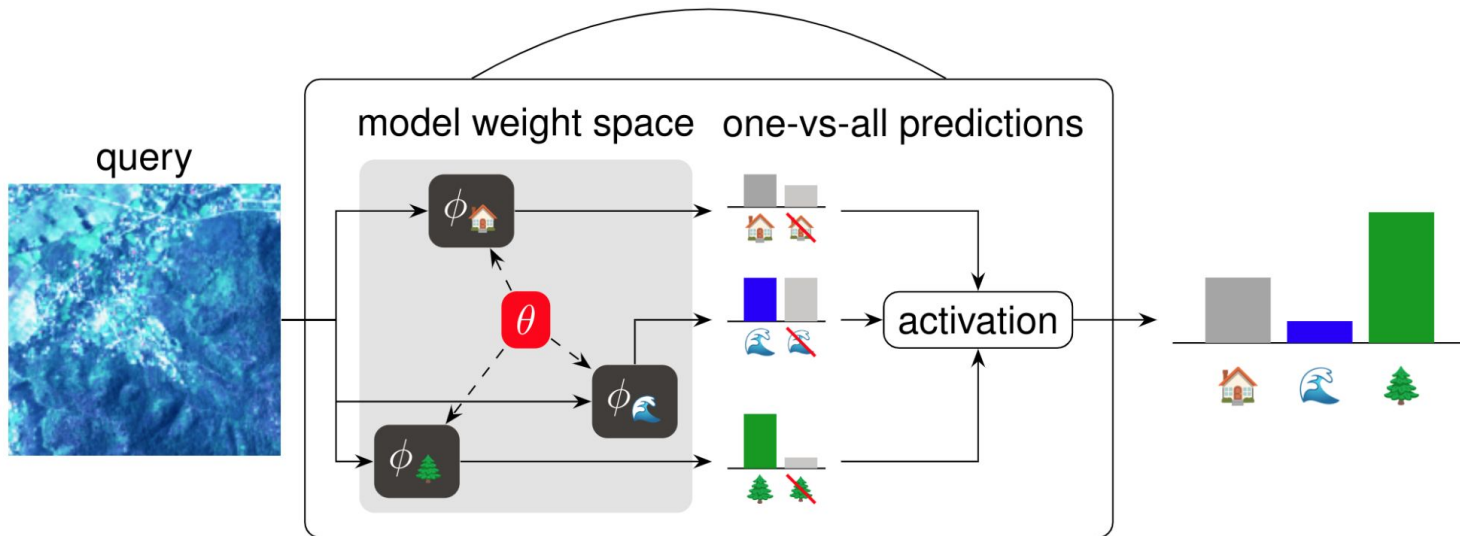
are deep neural networks with 11-million parameters



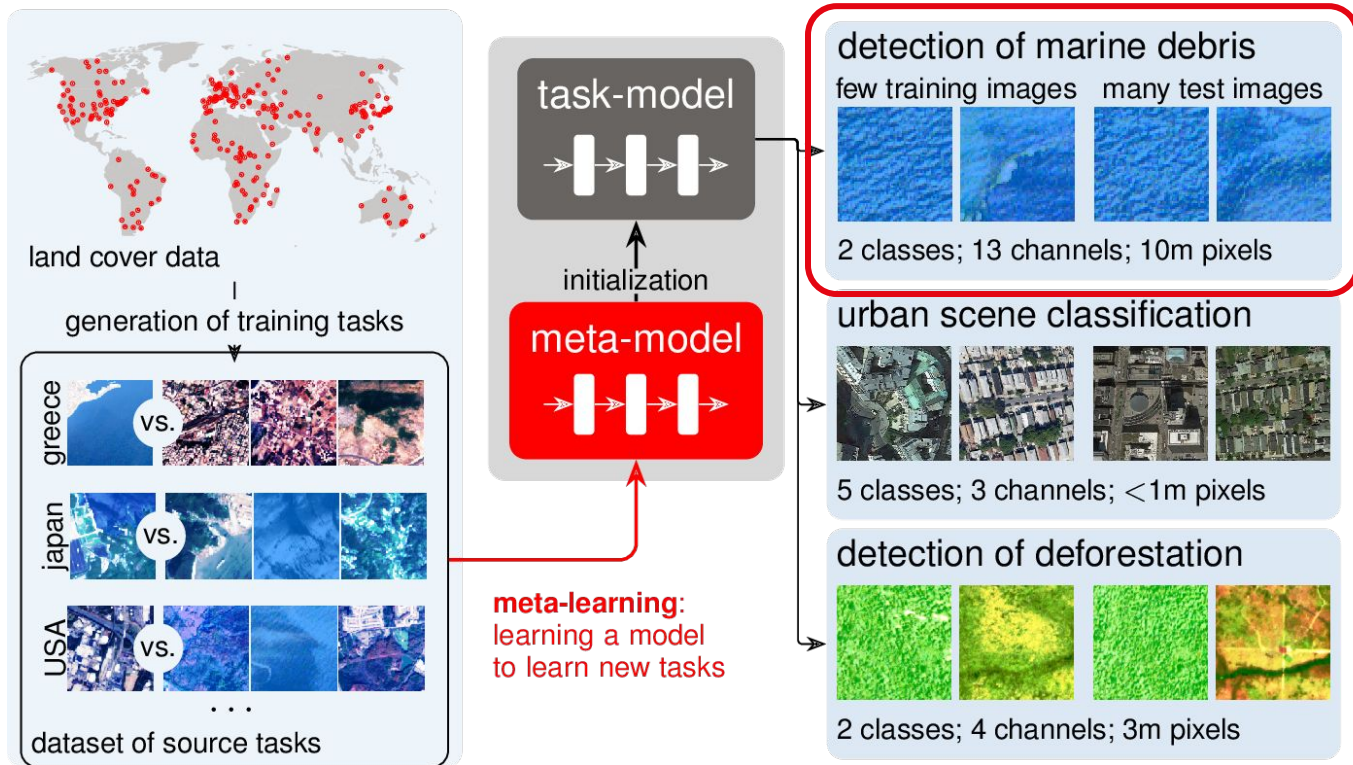
From binary to multi-class problems



The multi-class task-model



Land Cover to Other Downstream Tasks



EPFL Satellite-based marine litter monitoring



proxy

Detection of Marine Debris



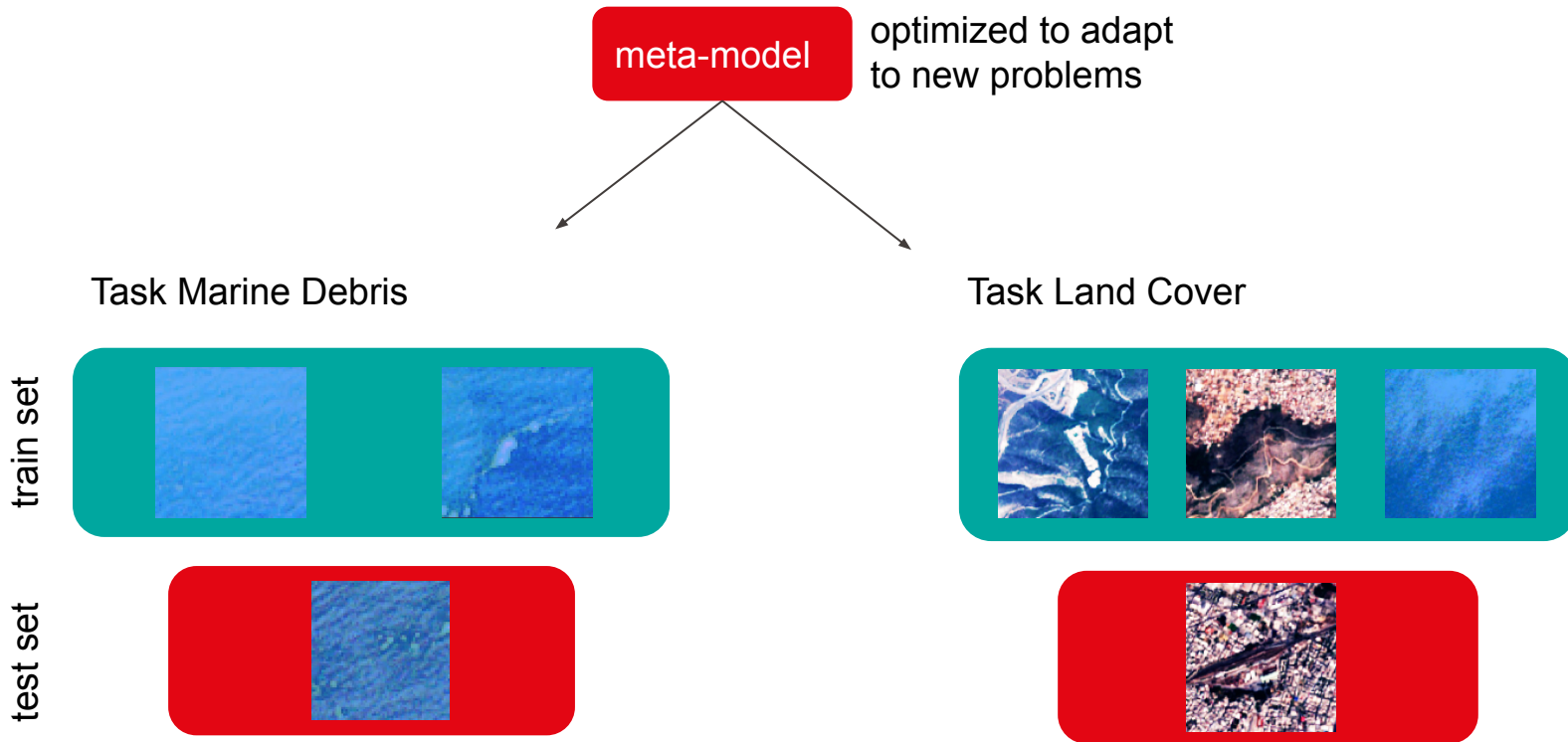
photo [@oihanech](#)

Oceanic processes aggregate debris on the water surface:
Here **windrows**

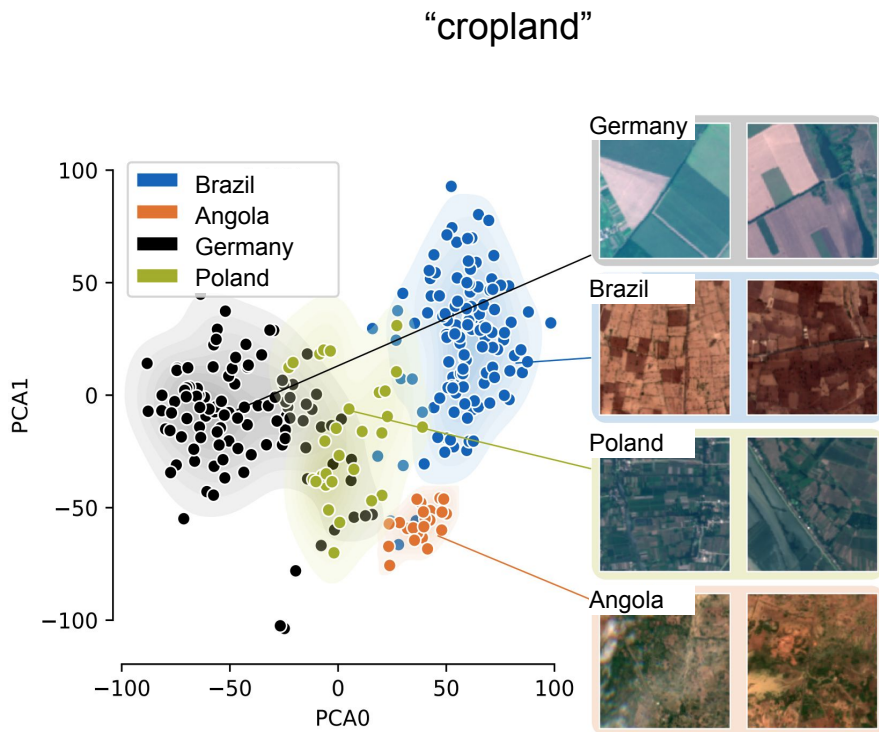
Windrows can contain plastic litter

Example:
16.2 tons in 68 working days collected plastic litter in the Bay of Biscay in 2018 by Ruiz et al., 2020

Connection between Land Cover and Marine Debris?



Cropland classification as different tasks



meta-model

optimized to adapt
to new problems

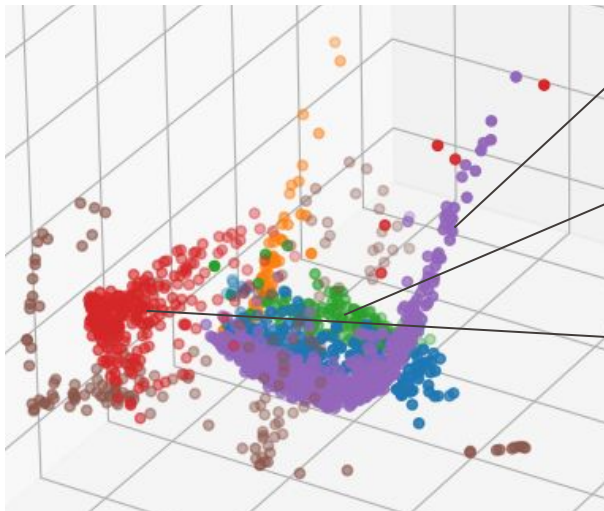
task-model

task-model

task-model

task-model

Different representations of
marine debris



meta-model

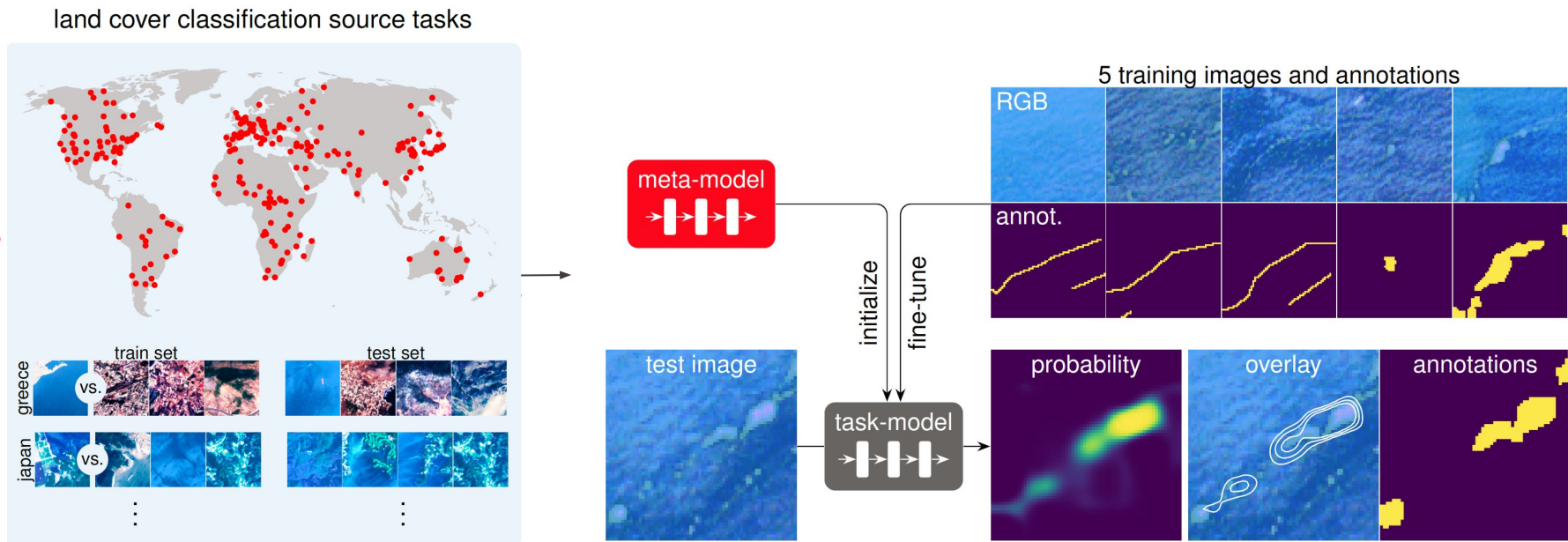
optimized to adapt
to new problems

task-model

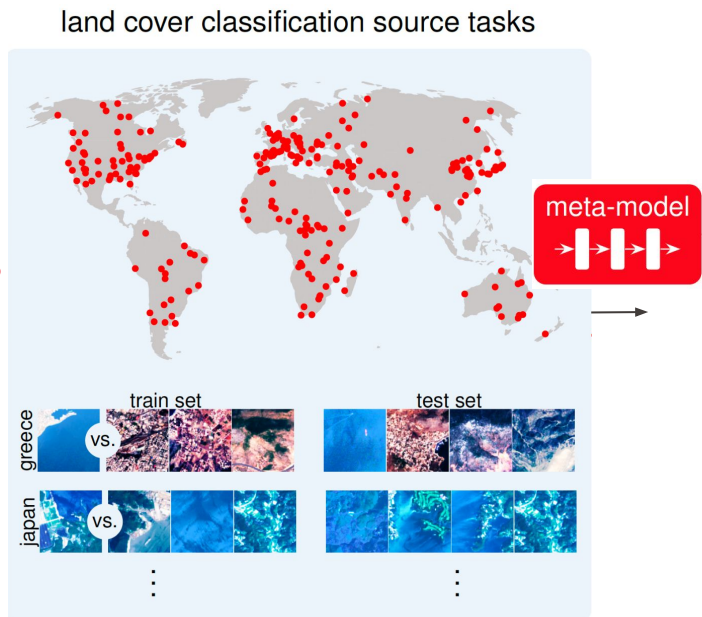
task-model

task-model

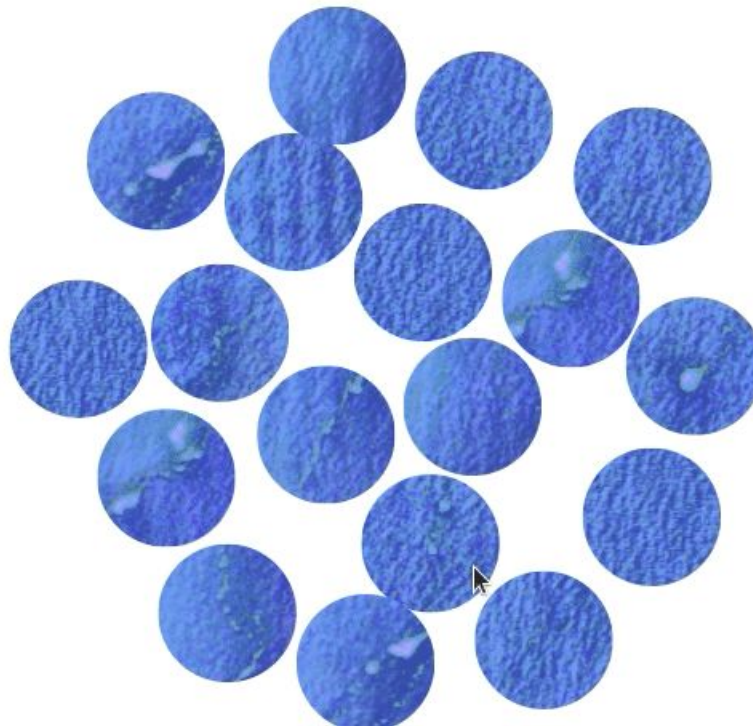
EPFL Meta-learned model fine-tuned for marine litter



Meta-learned model fine-tuned for marine litter detection



single-shot (1-sample per class) classification



EPFL Conclusion

- Meta-Learning as an algorithm to to “learn” new problems from a dataset of datasets.
- For geographic data, we represent the Earth as a “dataset of tasks” or a “dataset of datasets”
- Promising framework, given that we, as humans, also learn from problems rather than individual observations
- Complementary to existing approaches towards single large big-data models that aim to capture all global representations in one model



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work with collaborators: Devis Tuia,
Benjamin Kellenberger, Sherrie Wang,
Ribana Roscher, Dilge Gül, Jamila Mifdal,
Raquel Carmo

Meta-learning data-efficient Machine Learning Models for Diverse Earth Observation Problems

Publications related to this presentation:

- Rußwurm, M., Wang, S., Körner, M. & Lobell, D. (2020). Meta-learning for Few-shot Land Cover Classification. In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pages. 788–796. EarthVision 2020 Best Paper Award.
- Rußwurm, M., Wang S. & Tuia D. (2022). Humans are Poor Few-shot Classifiers. In IGARSS 2022 IEEE International Geoscience and Remote Sensing Symposium
- Rußwurm, M., & Tuia D. (2022). Instance norm improves meta-learning in class-imbalanced land cover classification. Distribution Shift Workshop 2022 at Conference and Workshop on Neural Information Processing Systems
- Mifdal, J., Longépé, N., Rußwurm, M. (2021). Towards Detecting Floating Objects on a Global Scale with Learned Spatial Features using Sentinel 2. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci., V-3-2021, 285–293, 2021, 169:421 – 435.