Efficient Learning for Earth Observation Applications with Self-Supervised Learning

Michael Mommert, Linus Scheibenreif, Joëlle Hanna, Damian Borth
University of St. Gallen

Deep Learning for Earth observation

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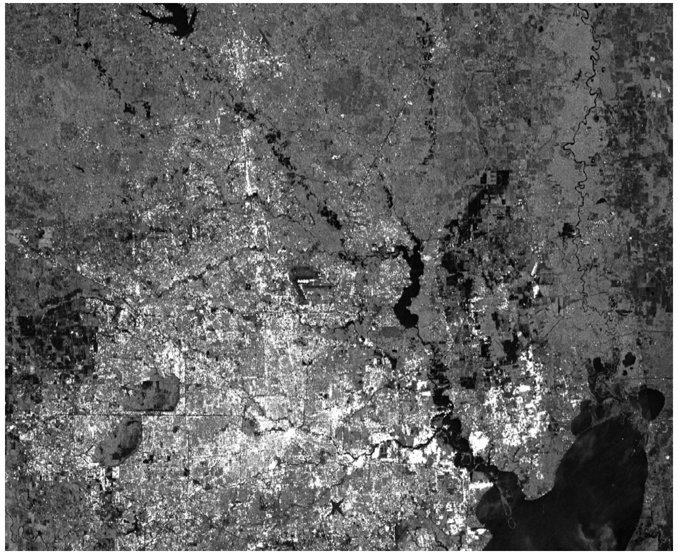
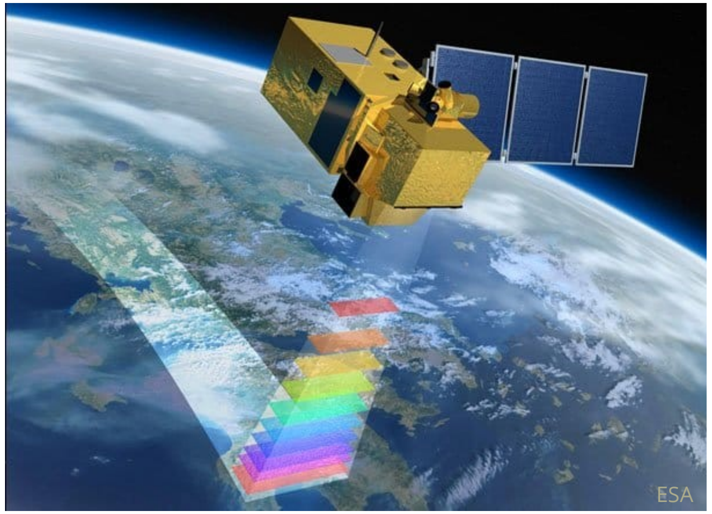
Earth observation data are highly complex (unstructured, multi-modal).





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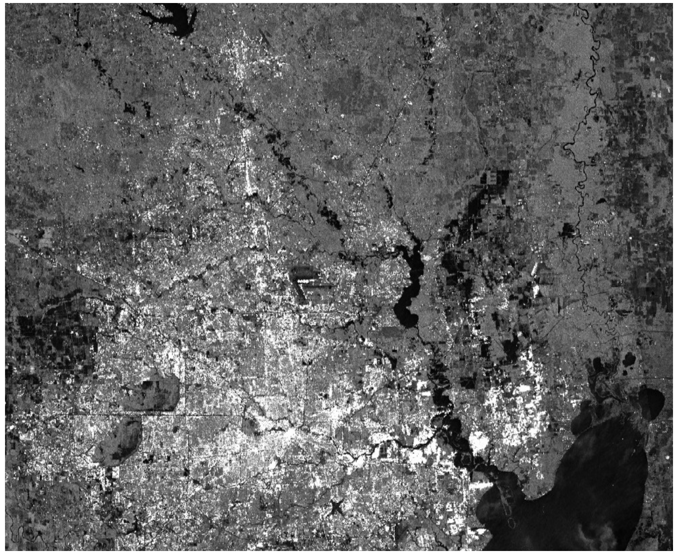
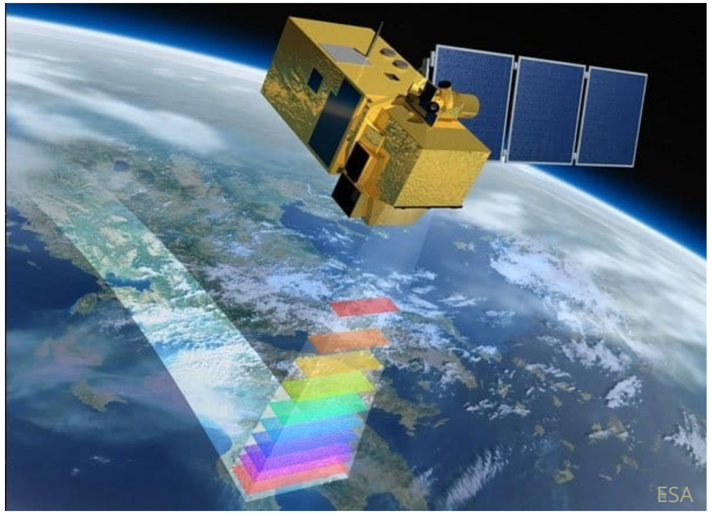
How can we analyze these vast amounts of data?





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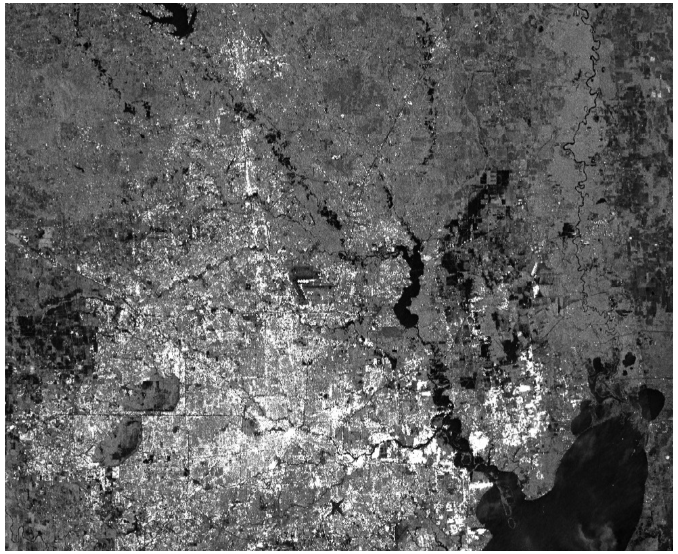
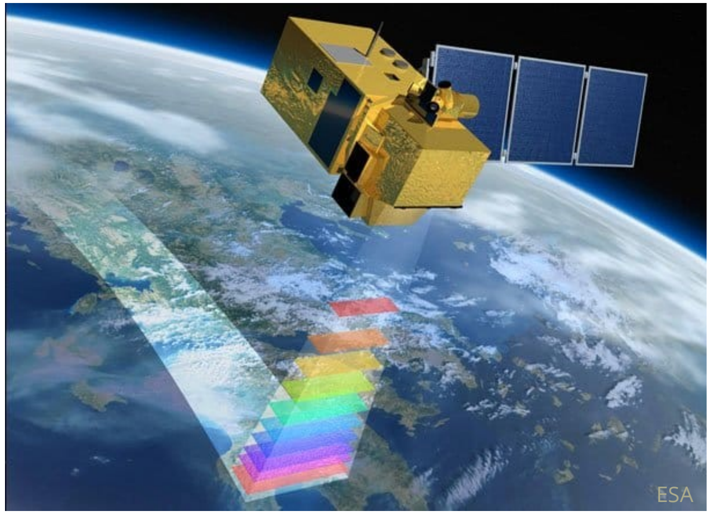


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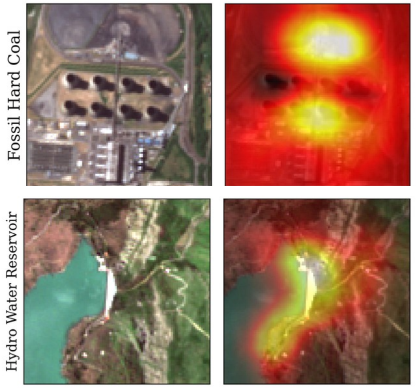
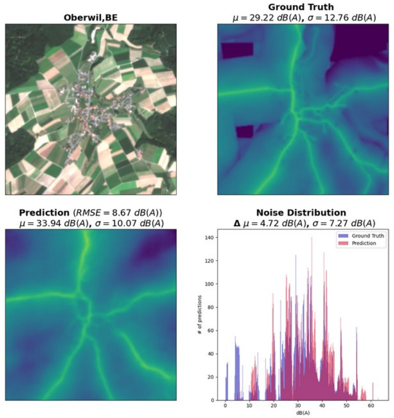
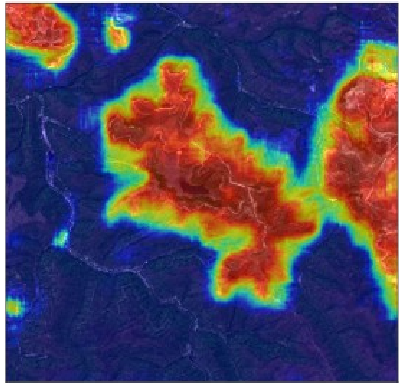
Deep Learning also offers the **flexibility** to deal with a range of different tasks.



Classification



Regression



Segmentation

Object Detection

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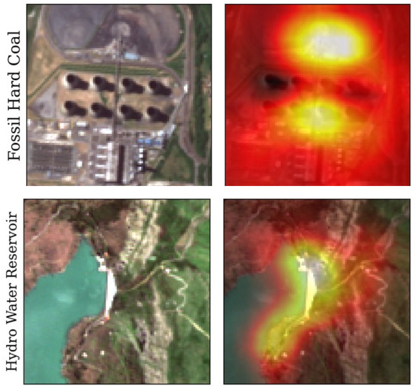

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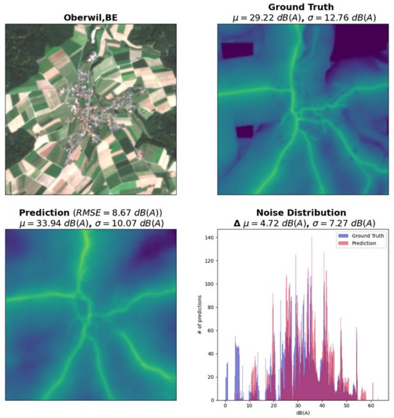

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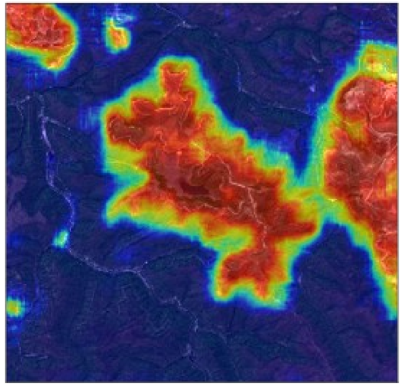

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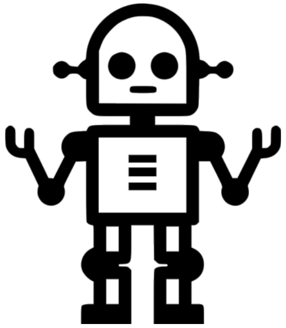
Supervised learning with Neural Networks



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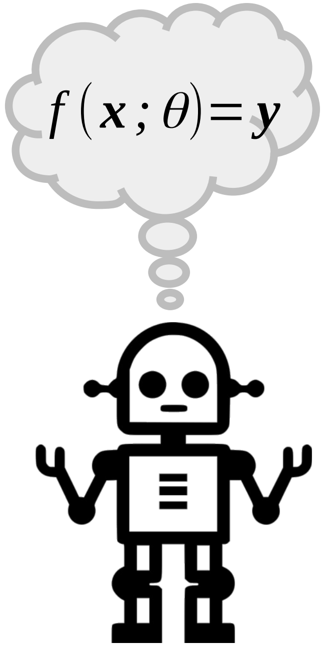

A machine learns a task from **annotated examples**.

Mathematically, it learns a function, f, that maps input data, $\boldsymbol{x}$, to the output, $\boldsymbol{y}$.

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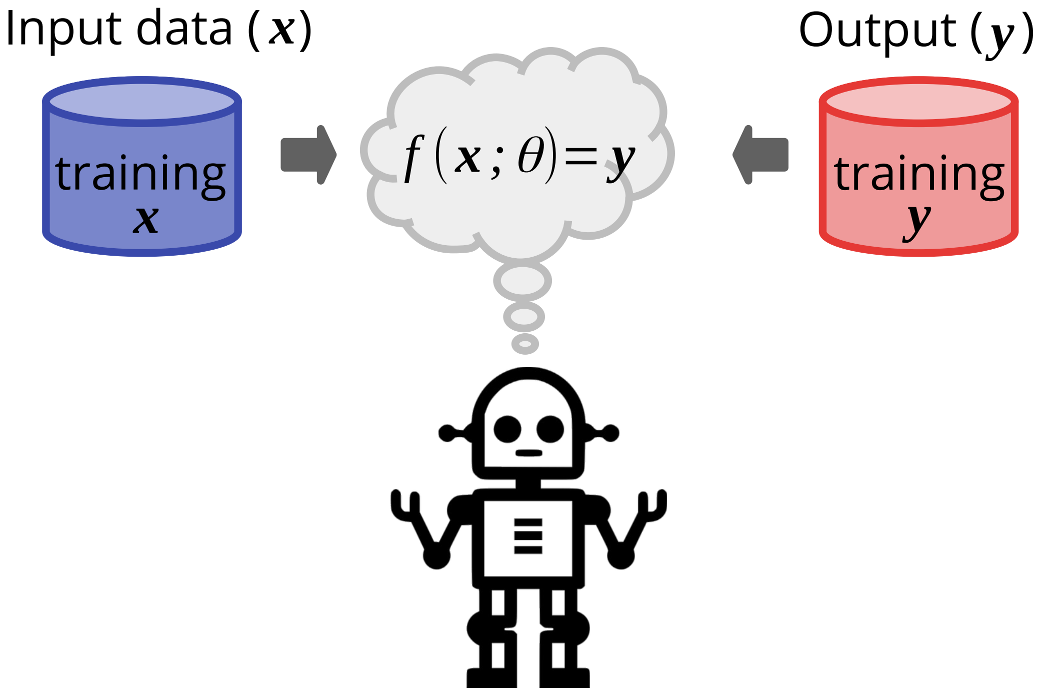

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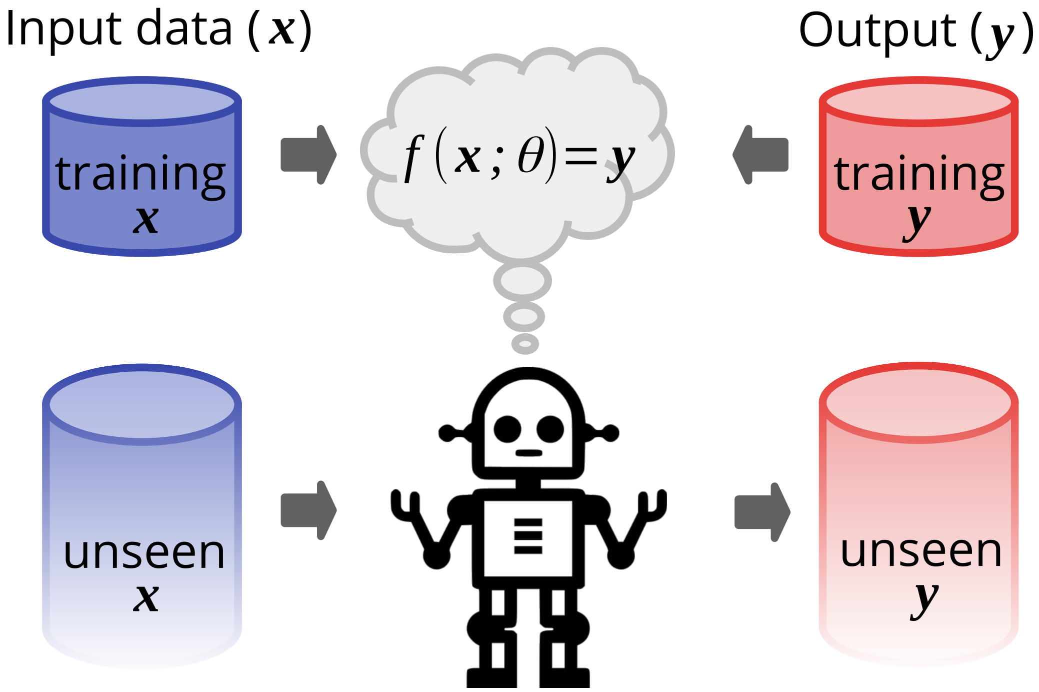

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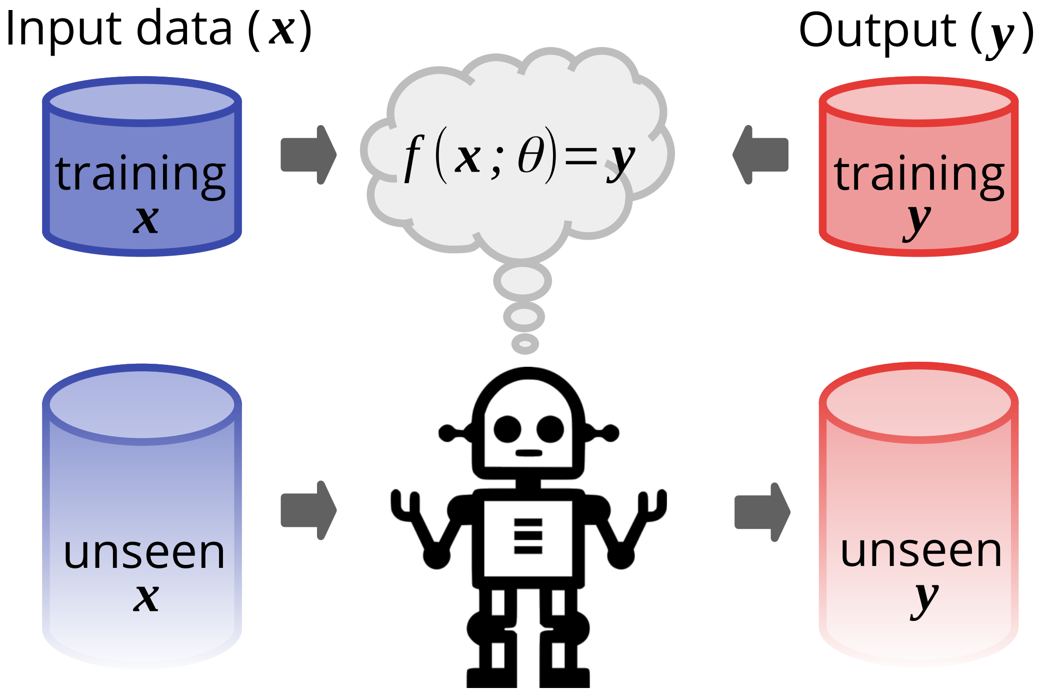

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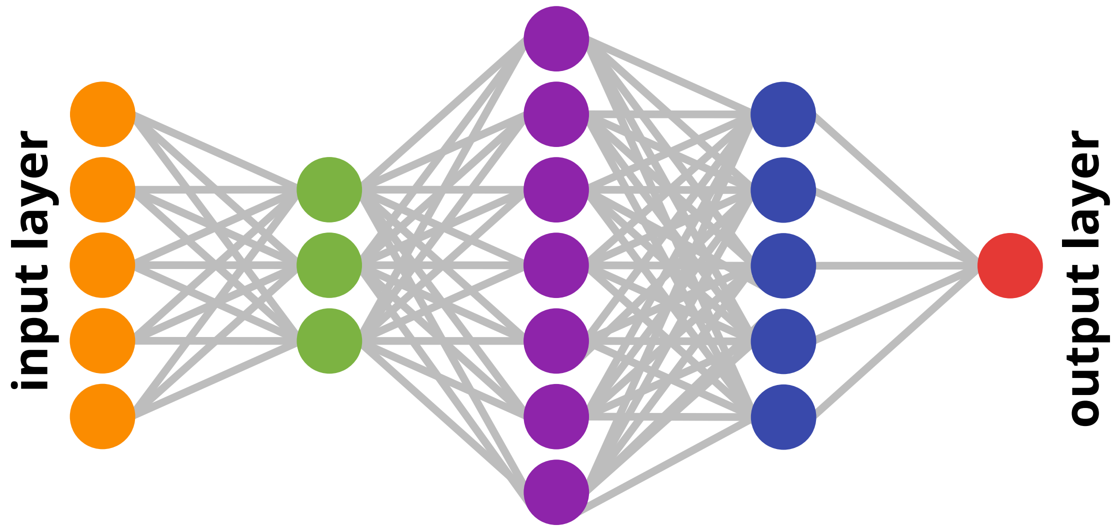
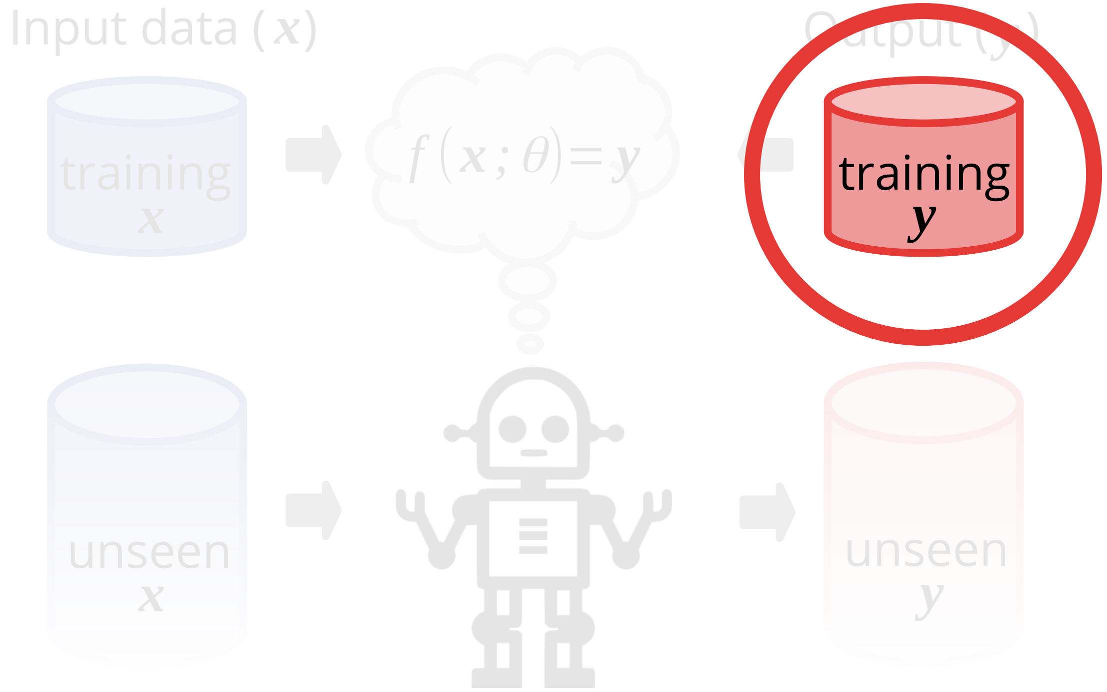


A Neural Network is a cascade of mathematical functions; each neuron contains learnable weights that represent the learned knowledge.

Supervised learning with Neural Networks



The availability of annotations typically represents the most important **bottleneck** in supervised learning.

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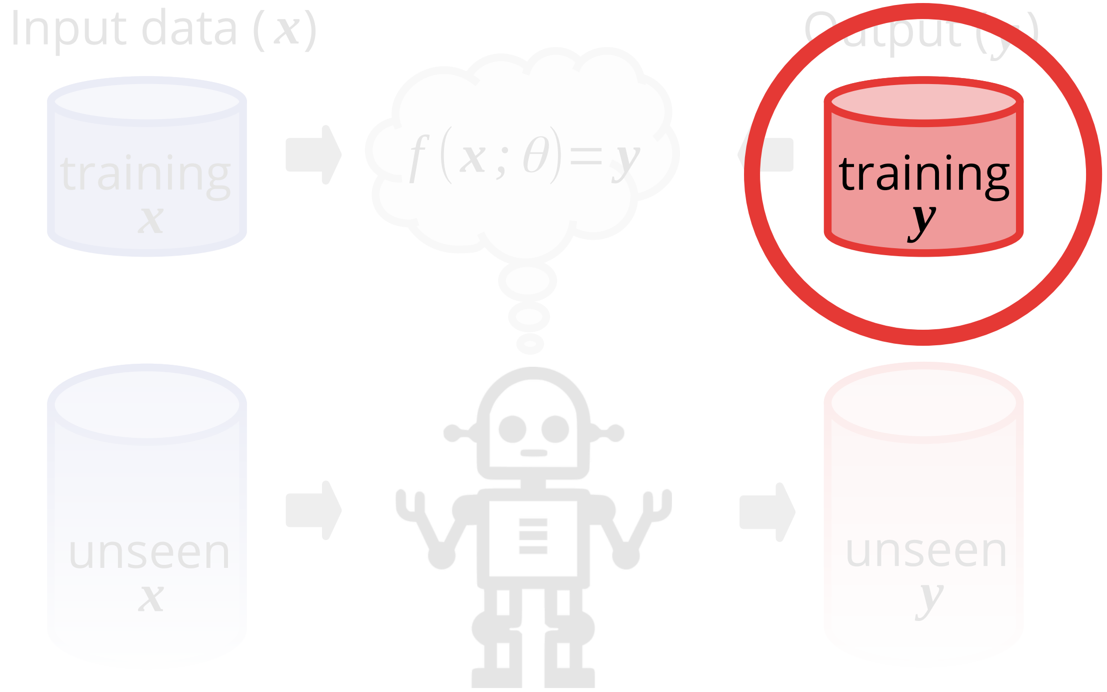

The availability of annotations typically represents the most important **bottleneck** in supervised learning.

Can we force the model to use the available annotations more **efficiently**?

Can we take advantage of the vast amounts of **unannotated data**?

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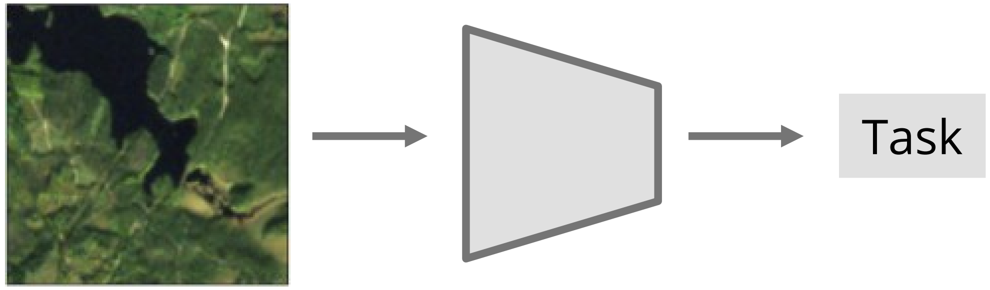

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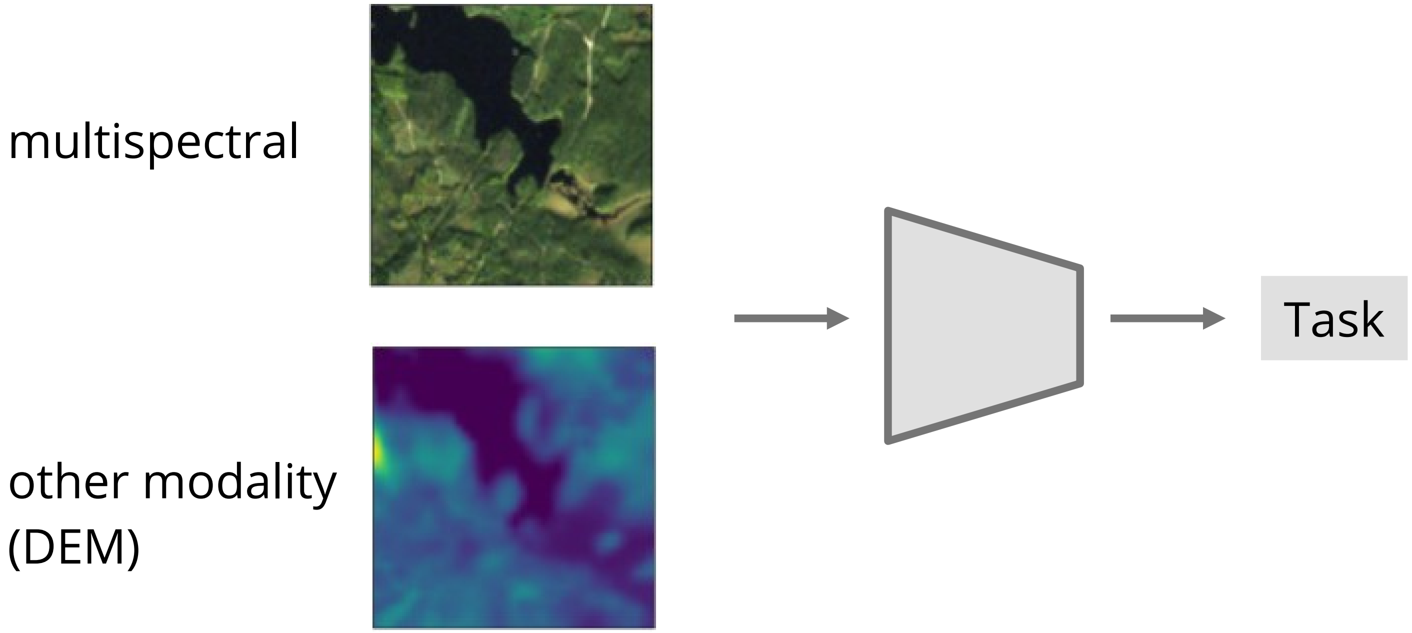

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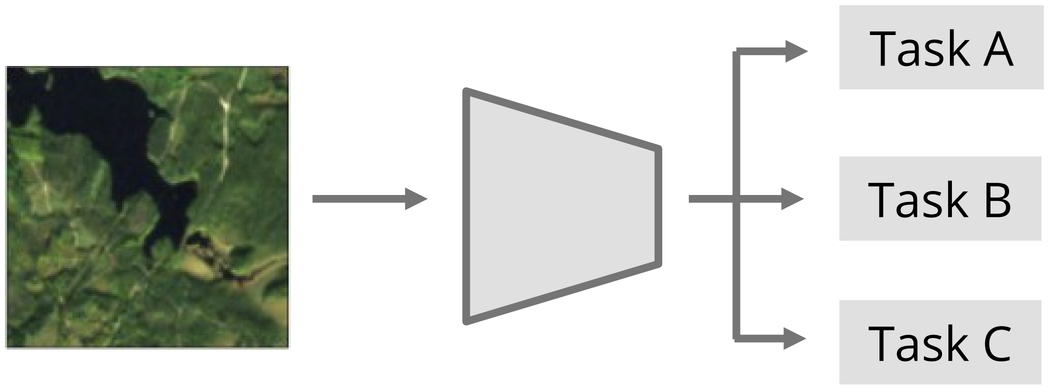

Hanna, J., Mommert, M., Scheibenreif, L. Borth, D., “Multitask Learning for Estimating Power Plant Greenhouse Gas Emissions from Satellite Imagery”, NeurIPS 2021 Tackling Climate Change with Machine Learning Workshop.

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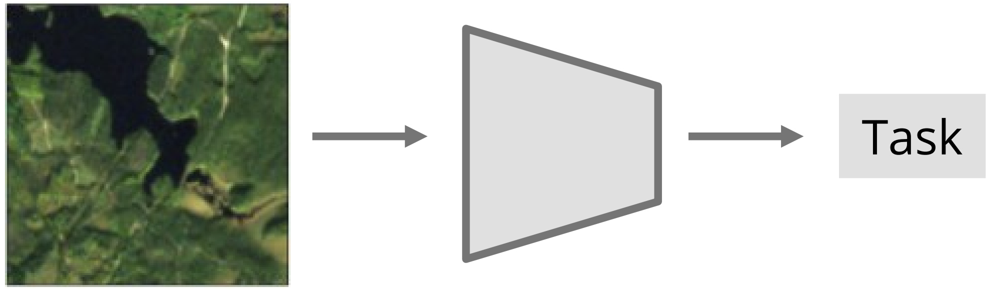

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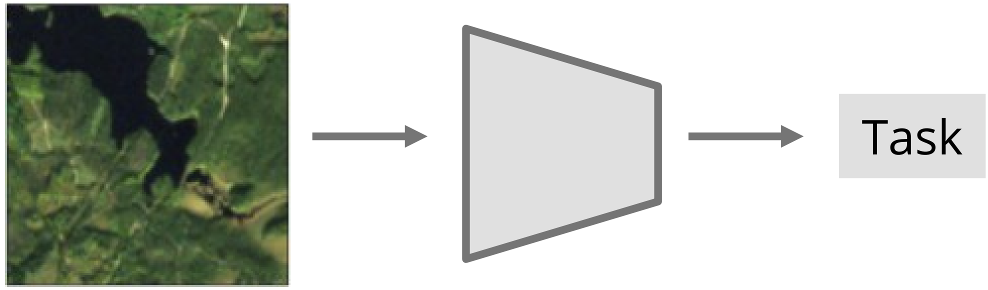

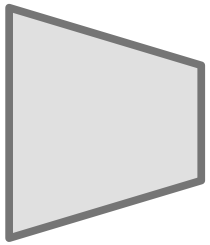

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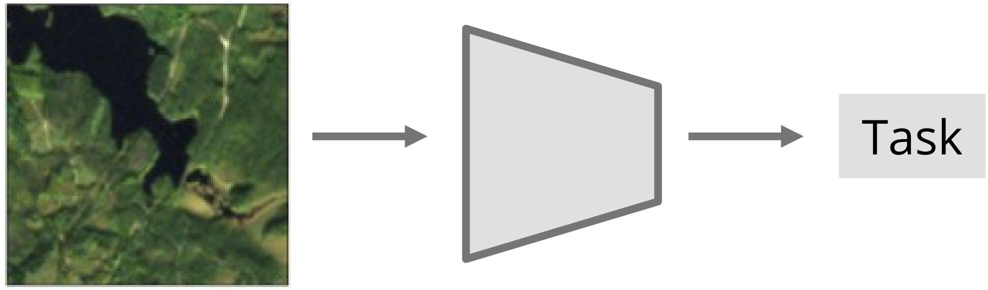
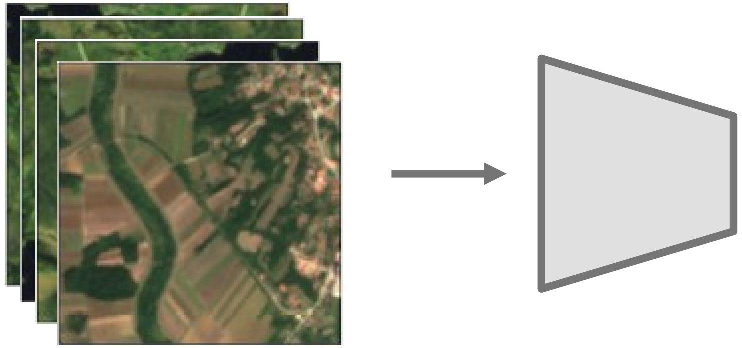


other dataset



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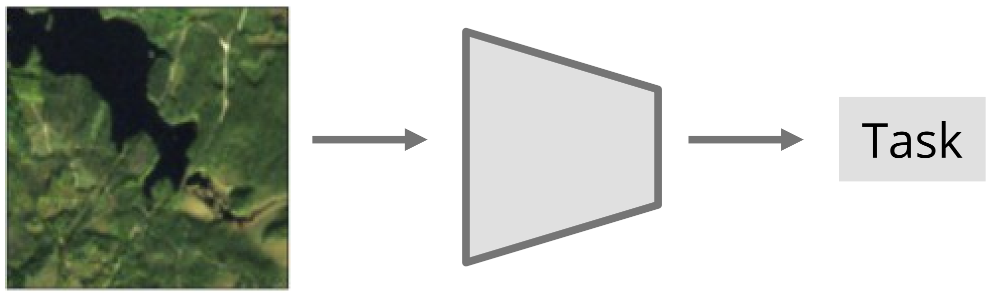

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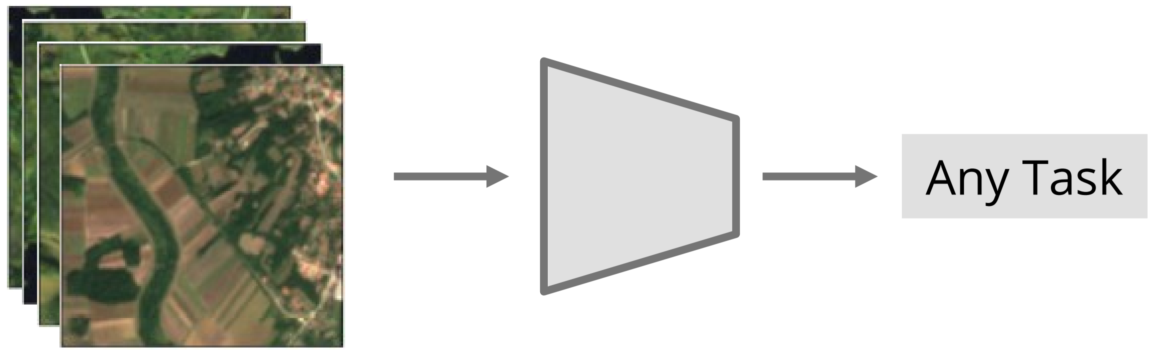

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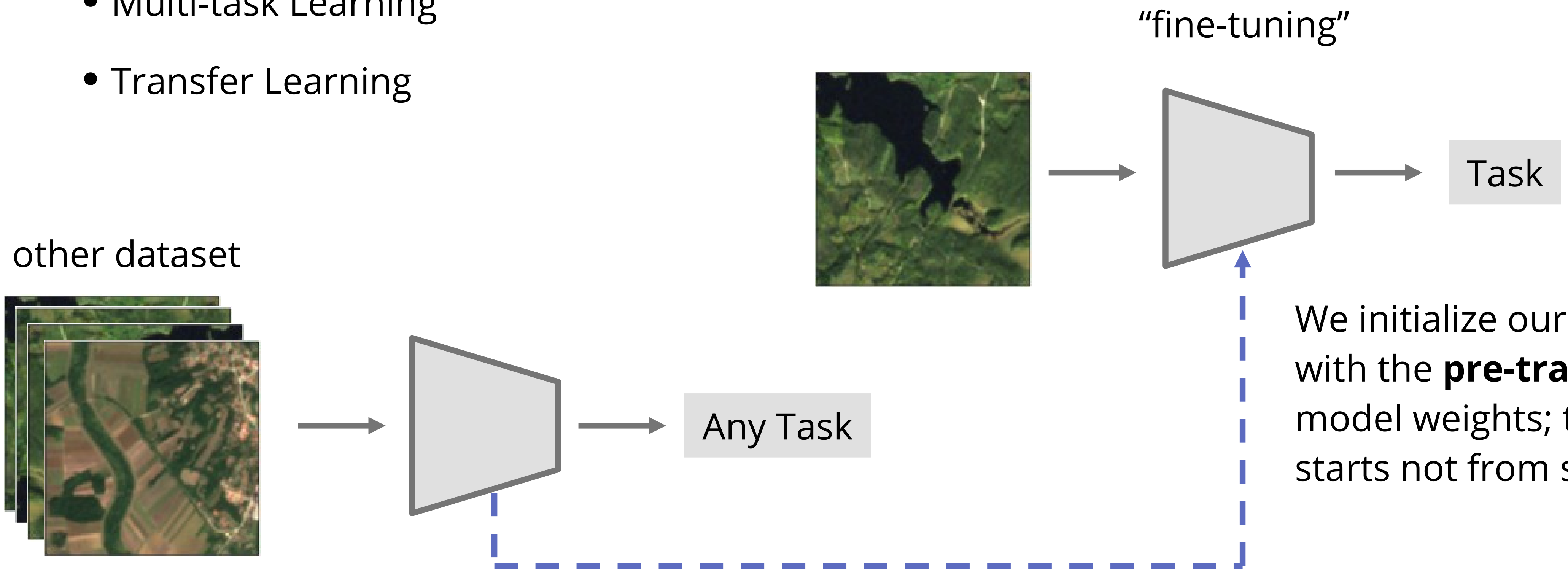

We initialize our model with the **pre-trained** model weights; training starts not from scratch!

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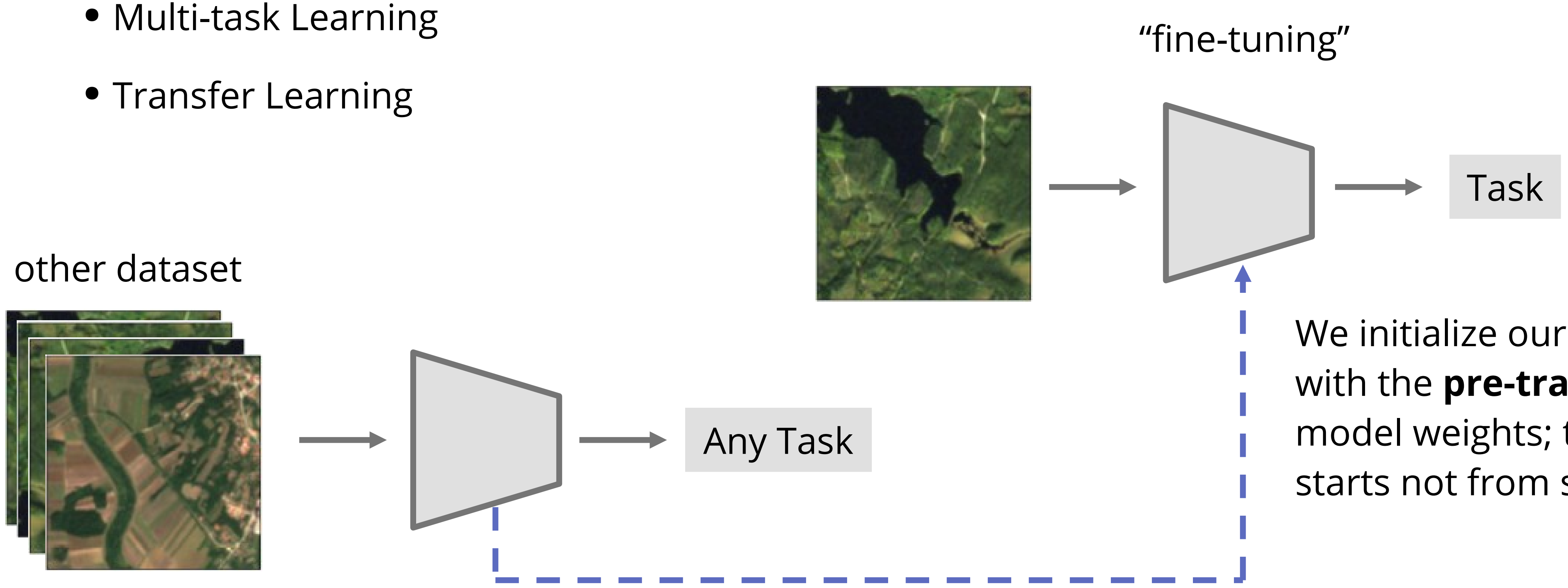
Can we pretrain a model from unannotated data?



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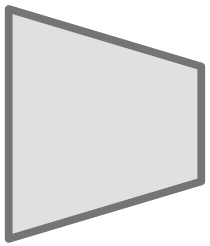
Contrastive self-supervised learning

Yes we can! SSL is able to learn **rich representations** from large amounts of unannotated data.

Contrastive learning setup (following SimCLR):



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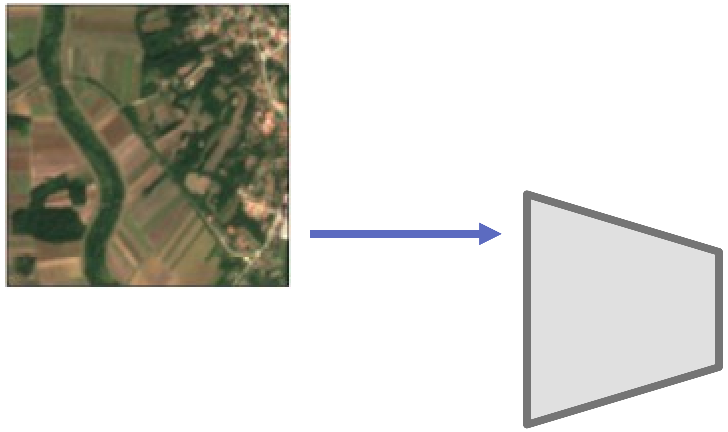

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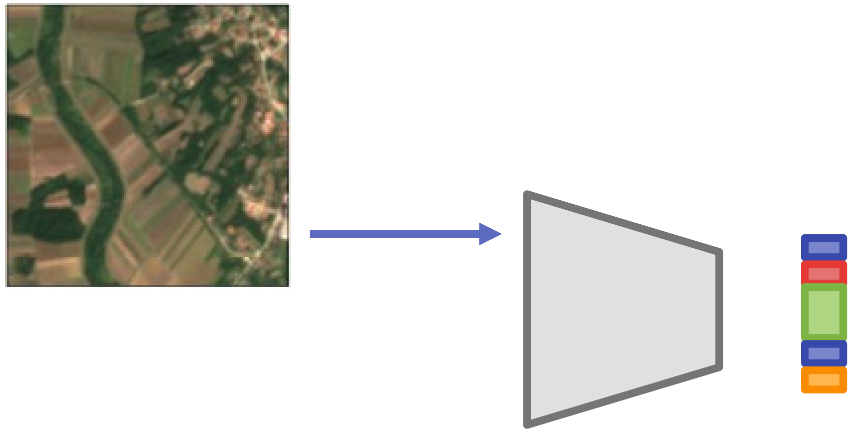

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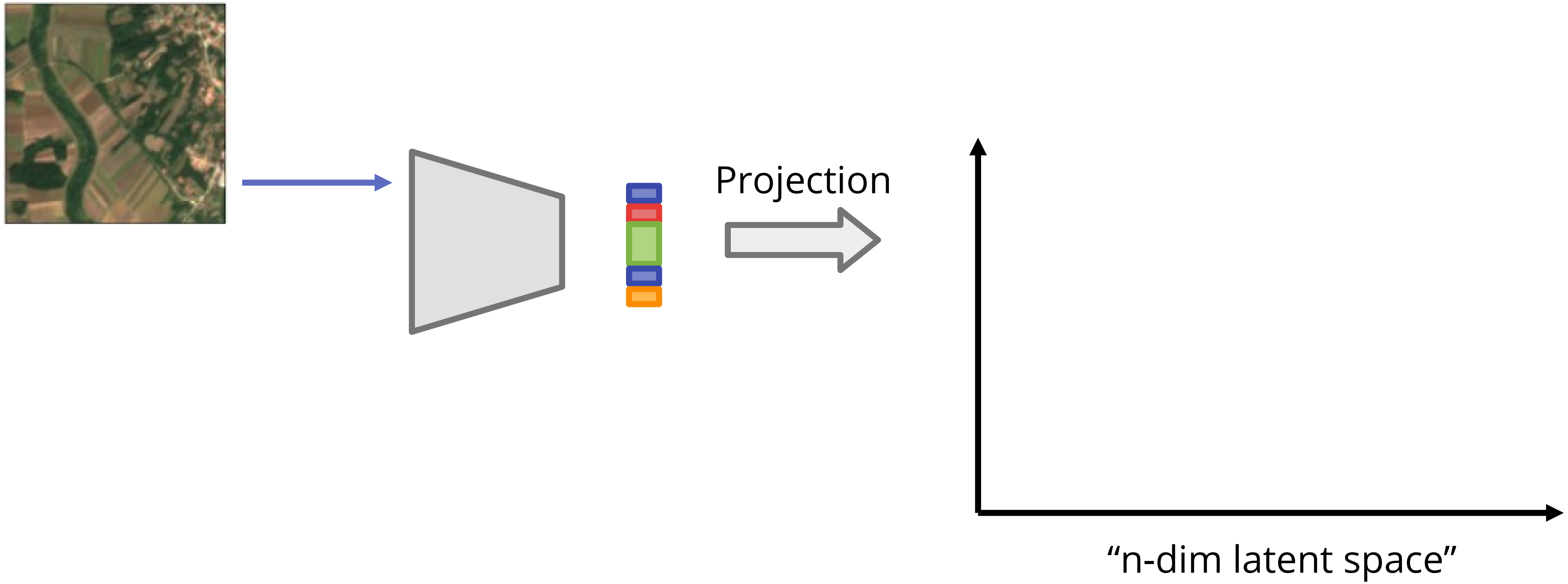

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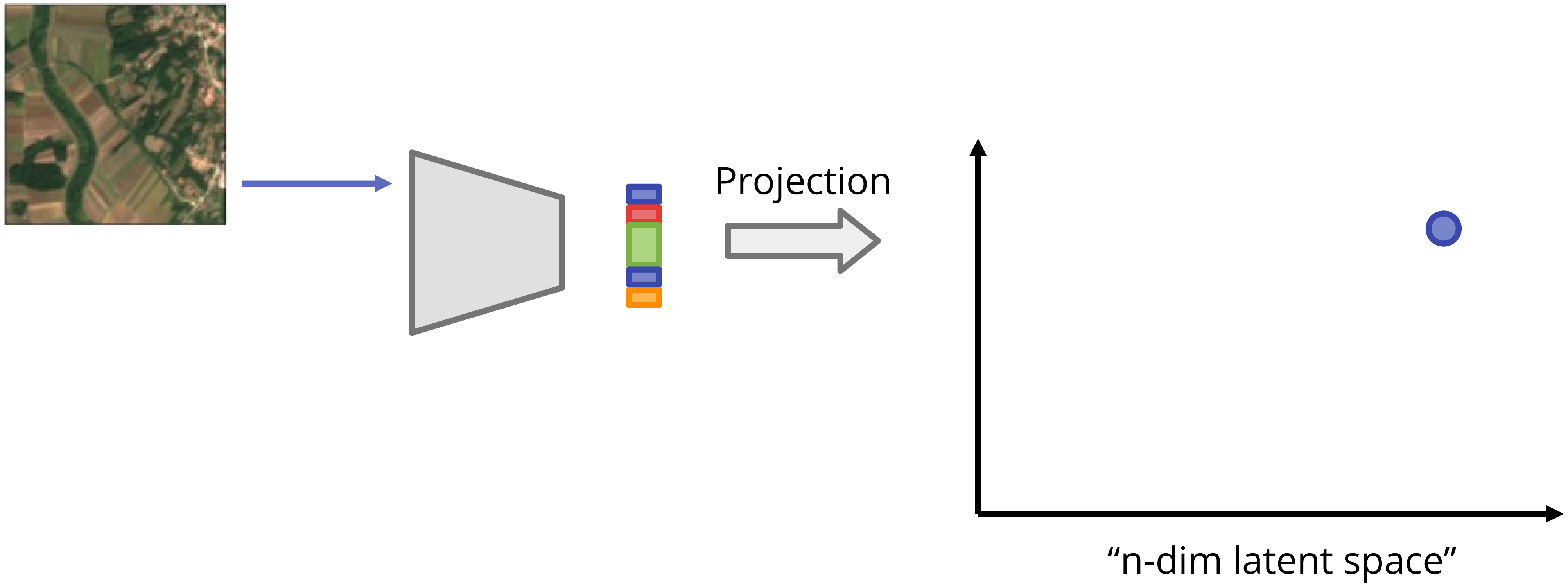

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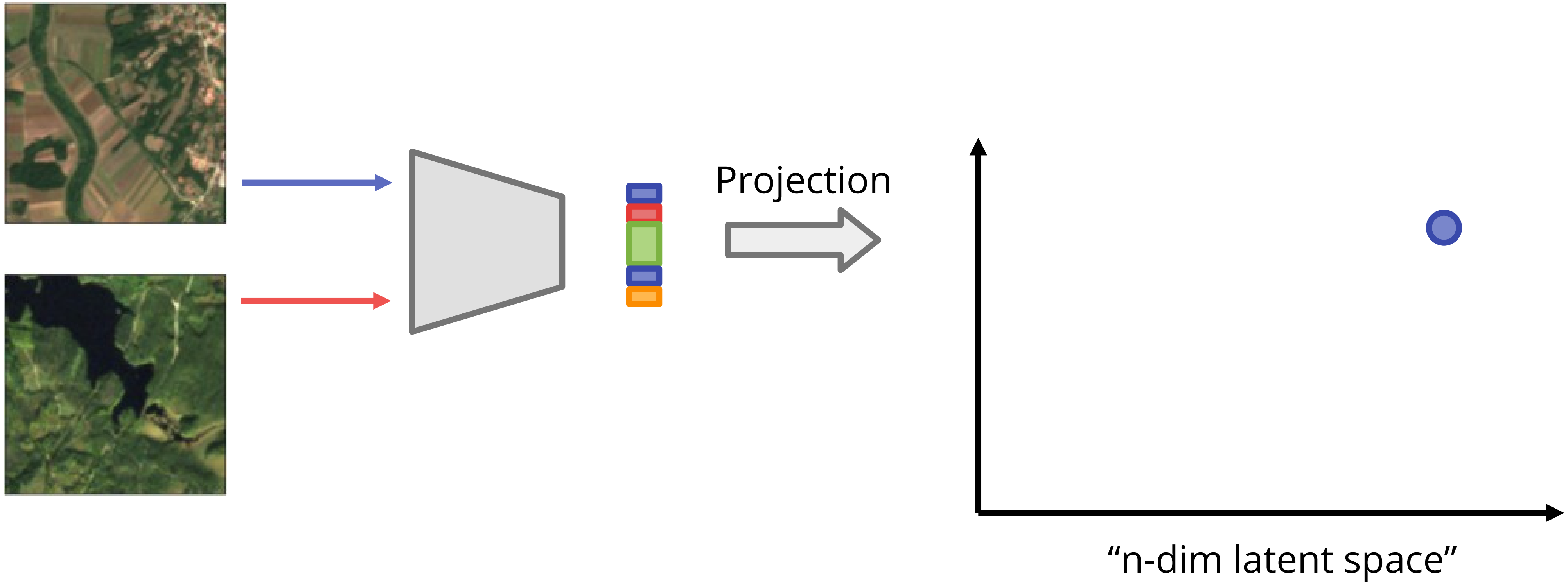

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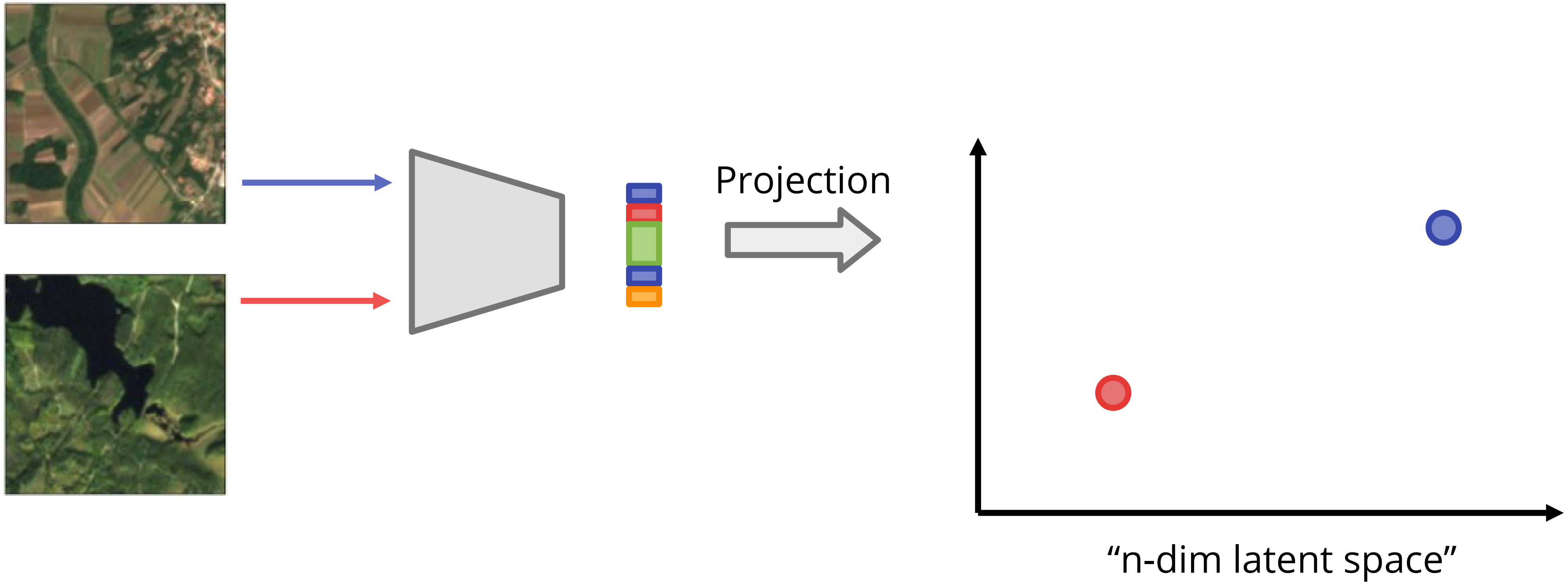

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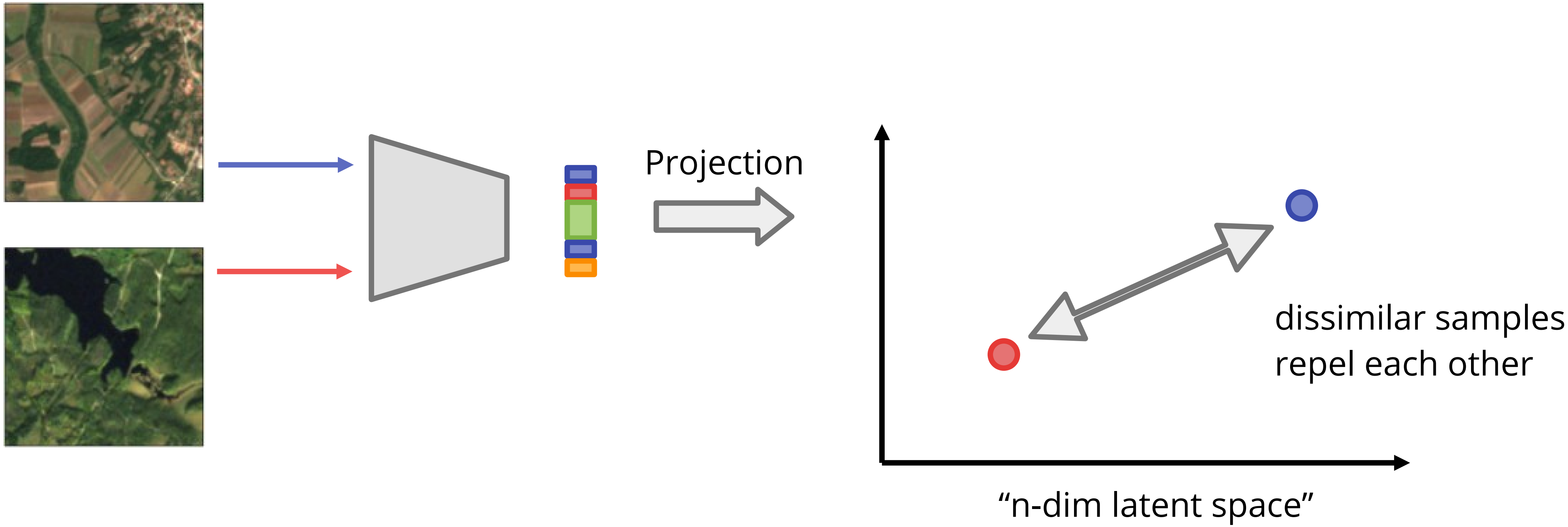

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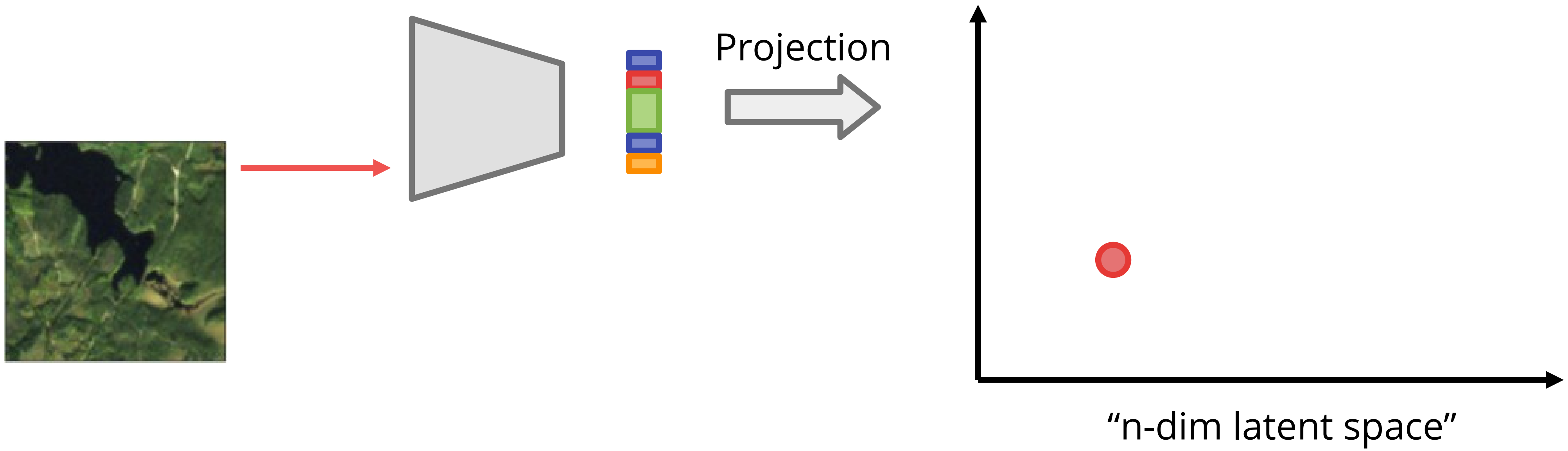

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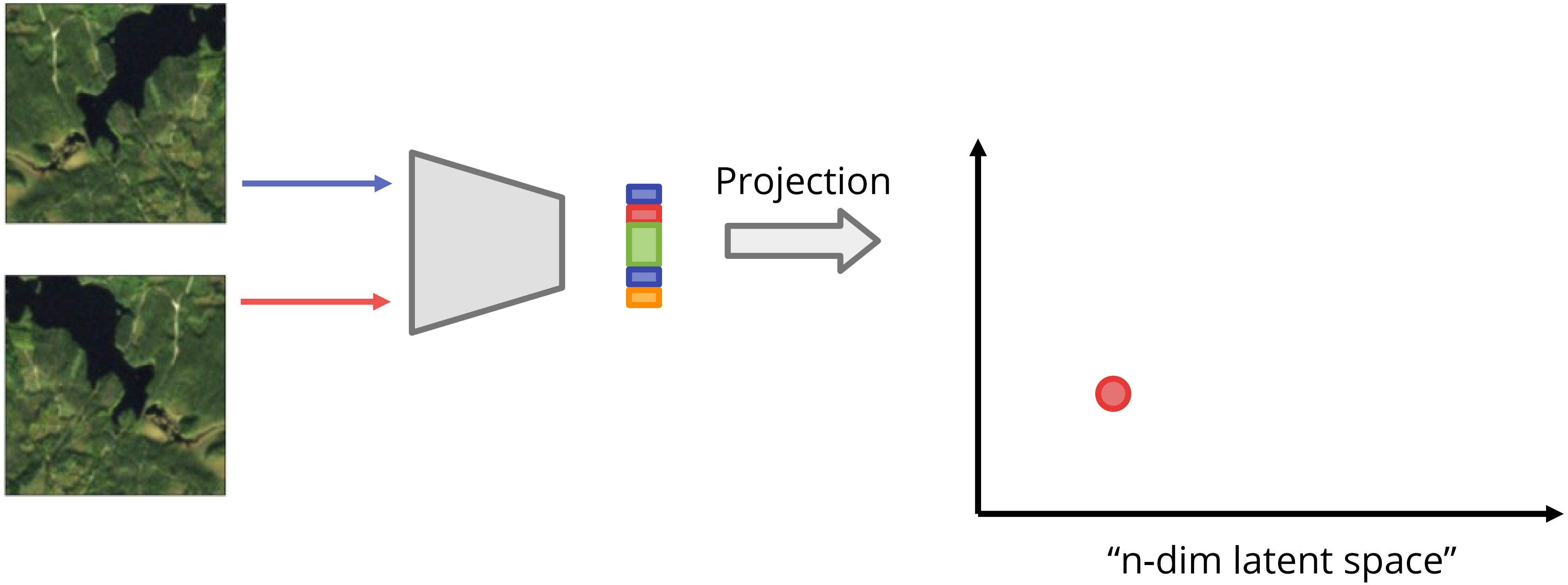

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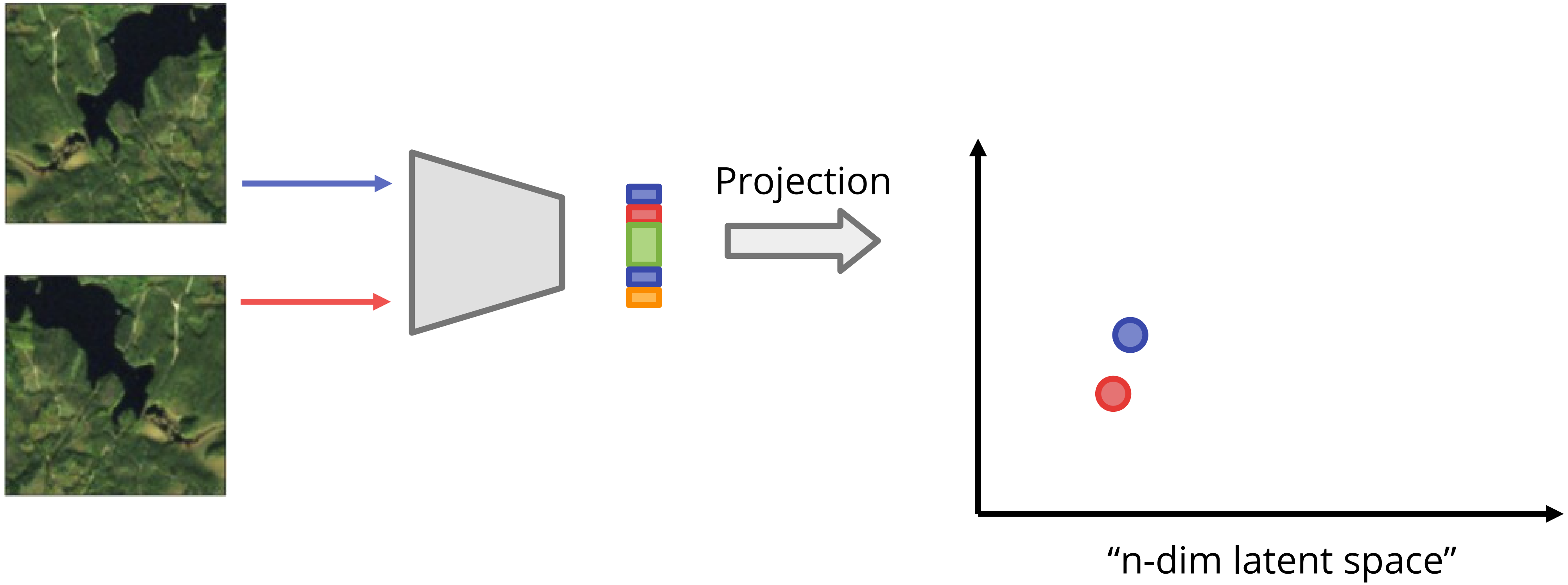

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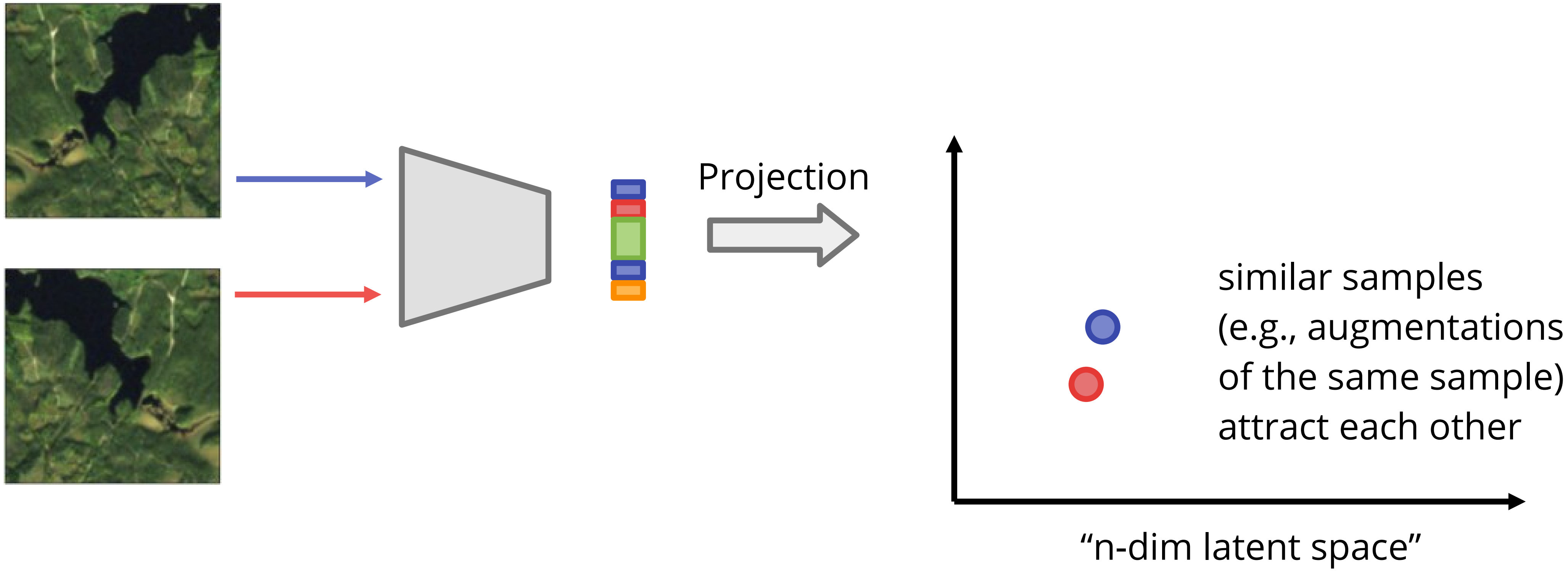

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Step 1: Pre-training

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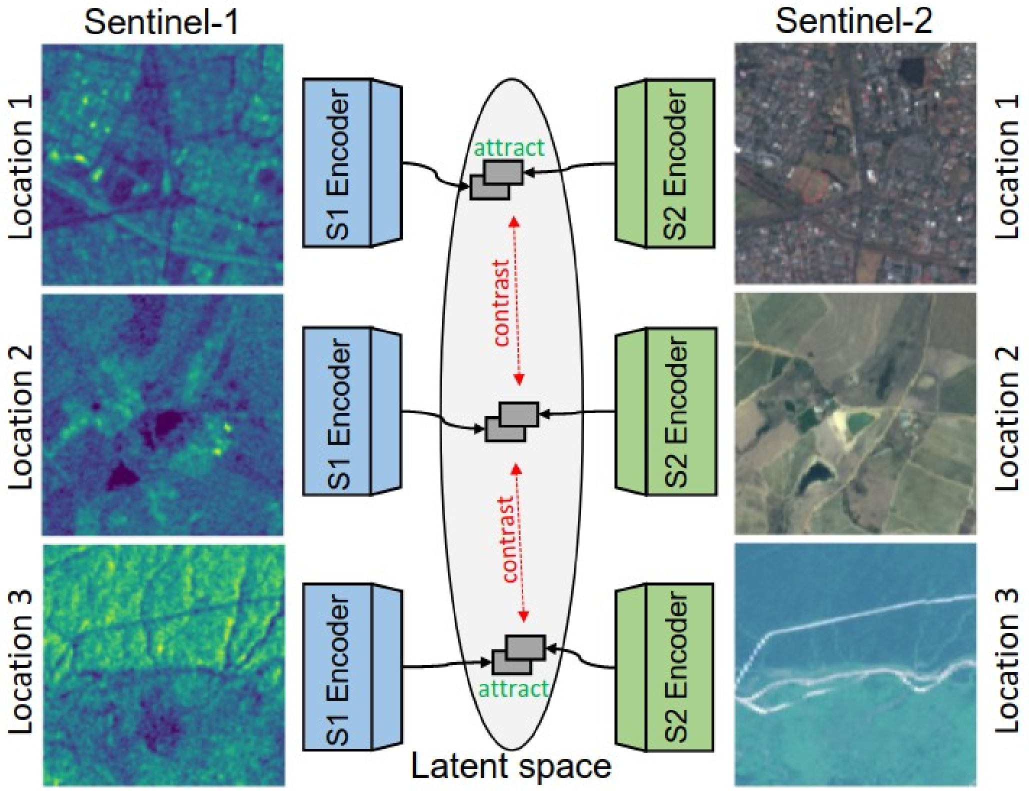

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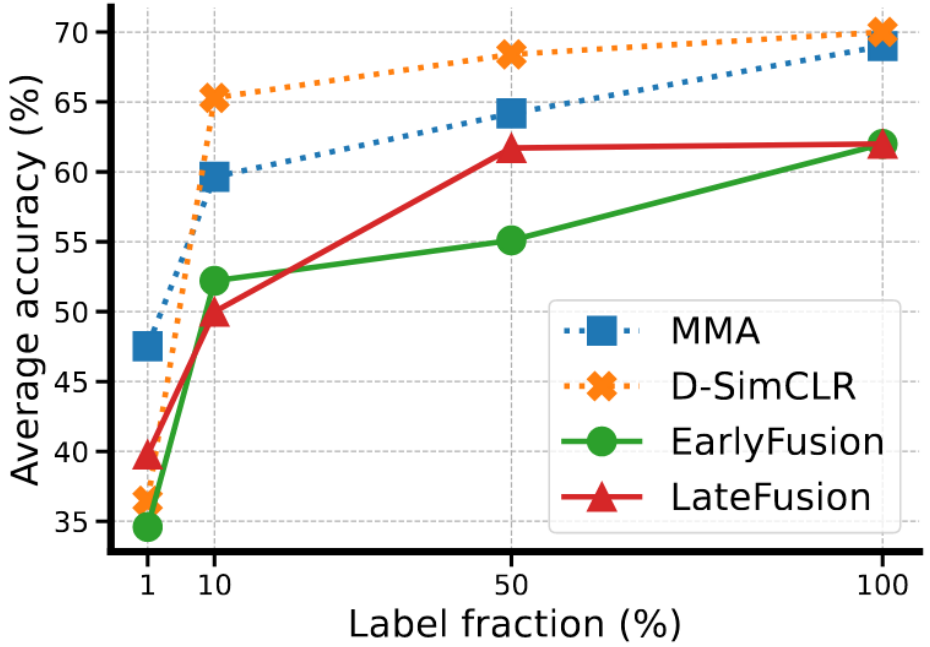

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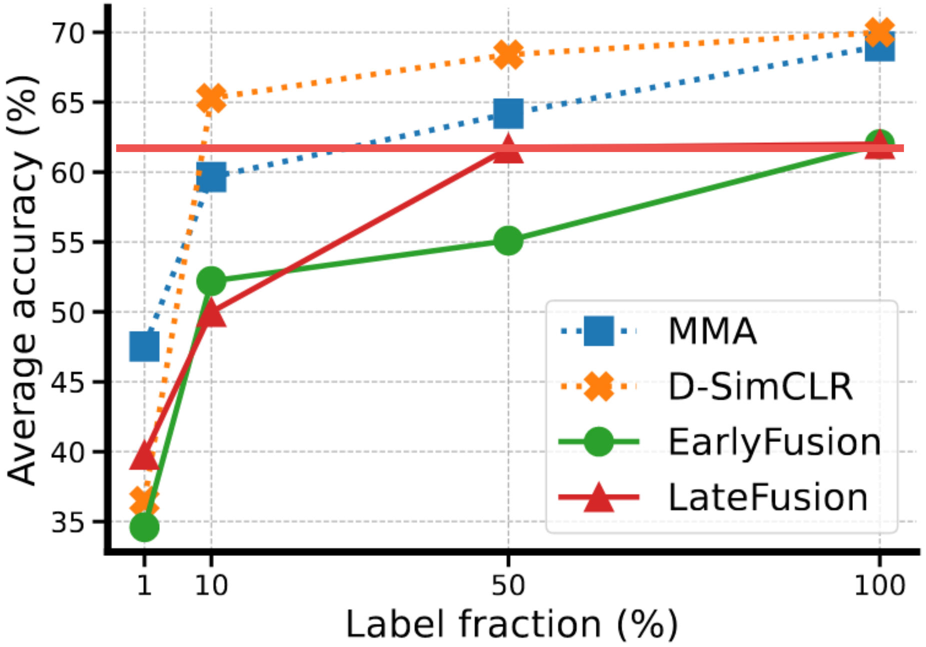

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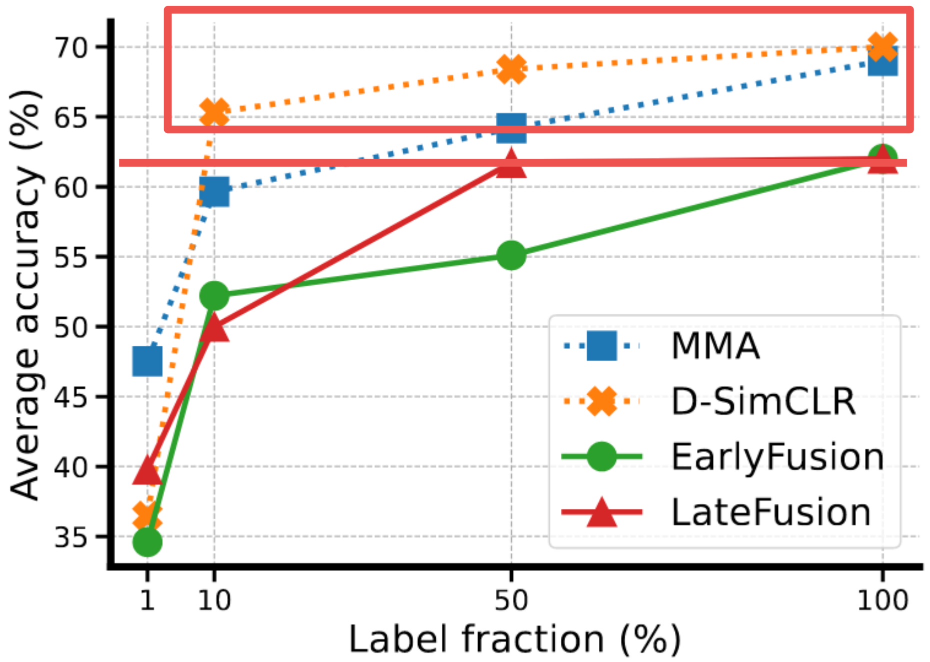
- Annotations from DFC2020 high-res (10m) land use/land cover maps, ~5k patches, 8 classes



Scheibenreif, L., Mommert, M., Borth, D., "Contrastive Self-Supervised Data Fusion for Satellite Imagery", ISPRS 2022.

Contrastive self-supervised learning for Earth observation

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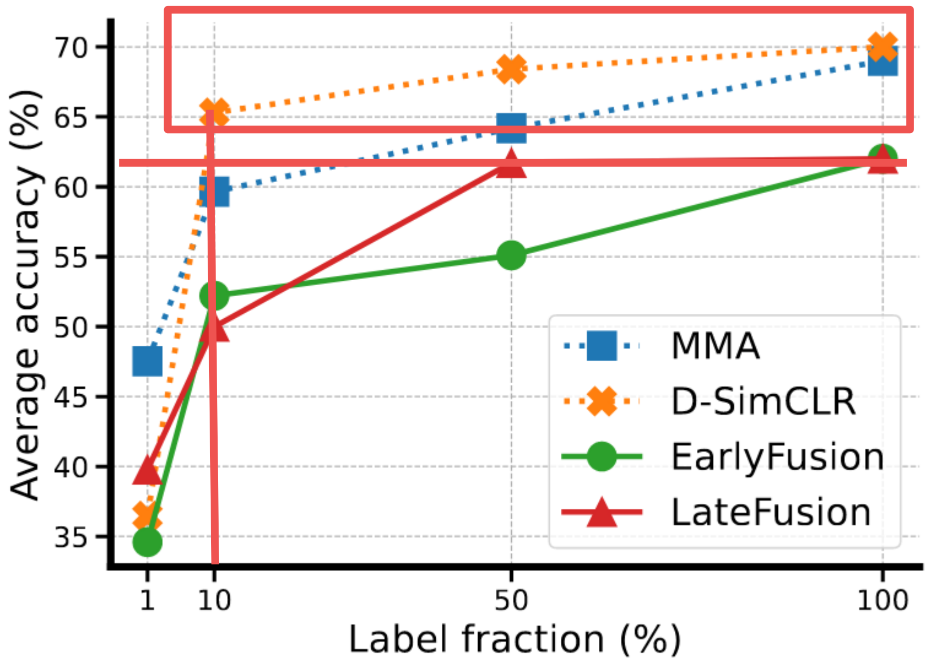

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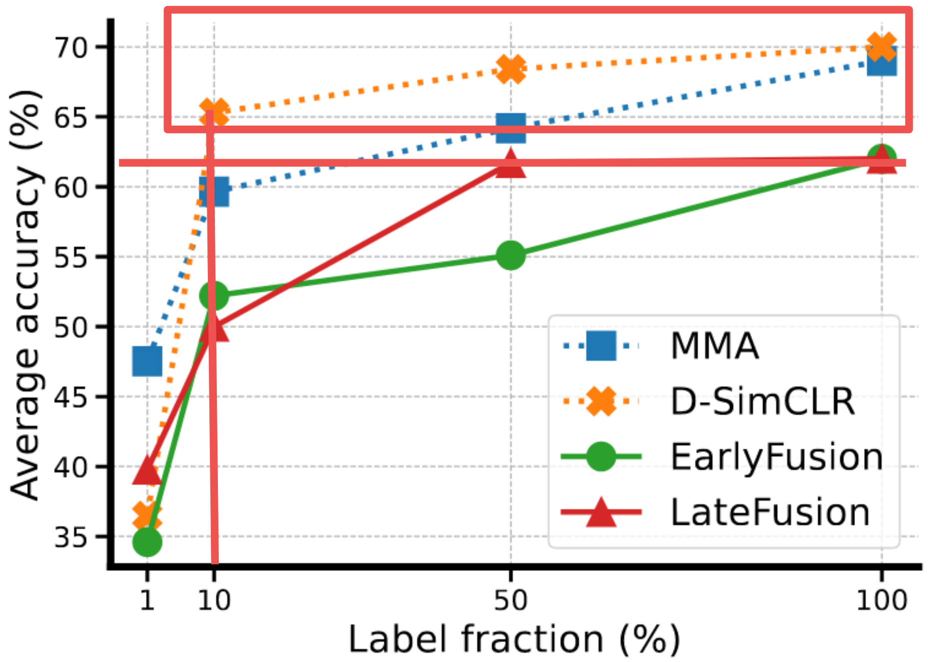
Contrastive self-supervised learning for Earth observation

Step 2: Fine-tuning on classification task

- Annotations from DFC2020 high-res (10m) land use/land cover maps, ~5k patches, 8 classes
- Main result: pretrained models outperform supervised baselines with only **10% of training data**



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Self-supervised Vision Transformers for Earth observation

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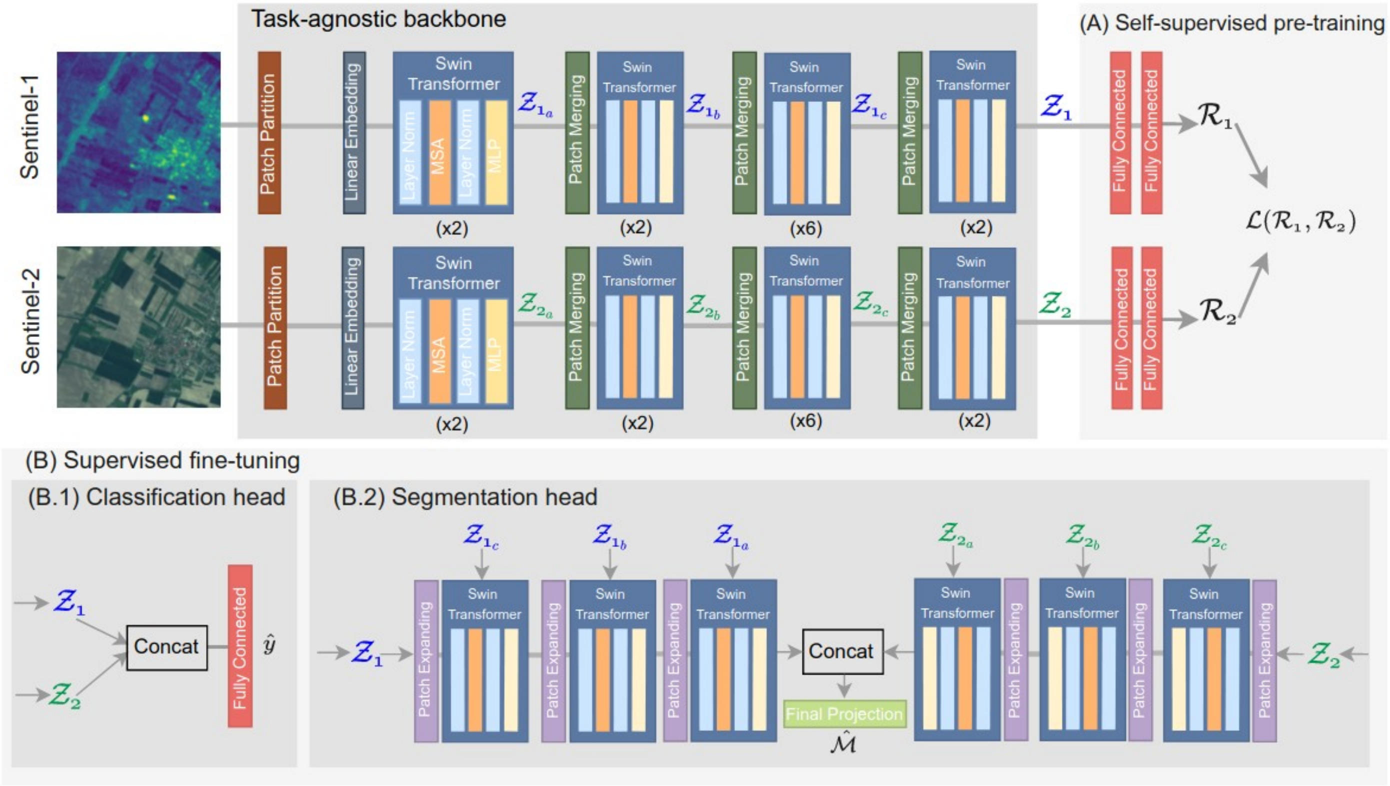
Self-supervised Vision Transformers for Earth observation



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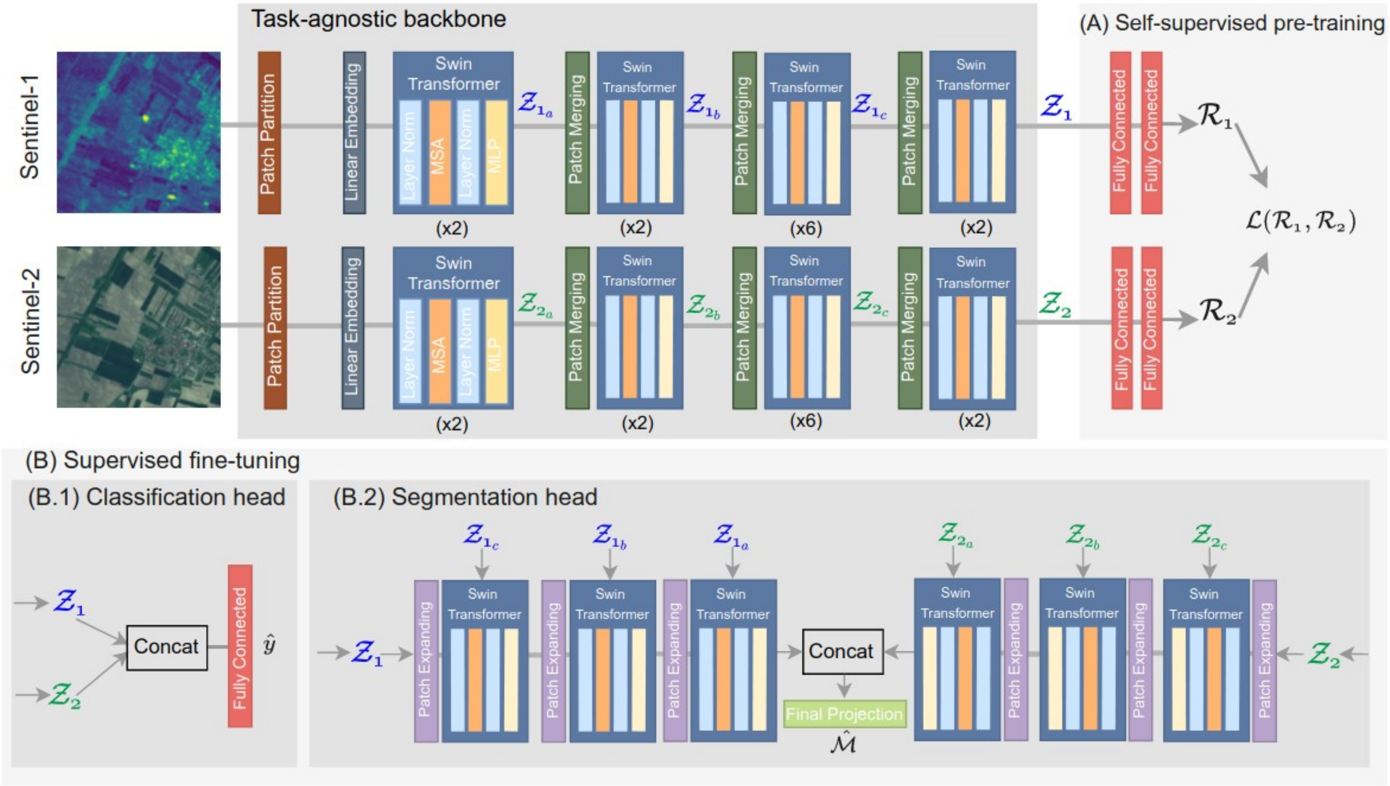
Self-supervised Vision Transformers for Earth observation

We retry our experiment with a **Transformer architecture**.



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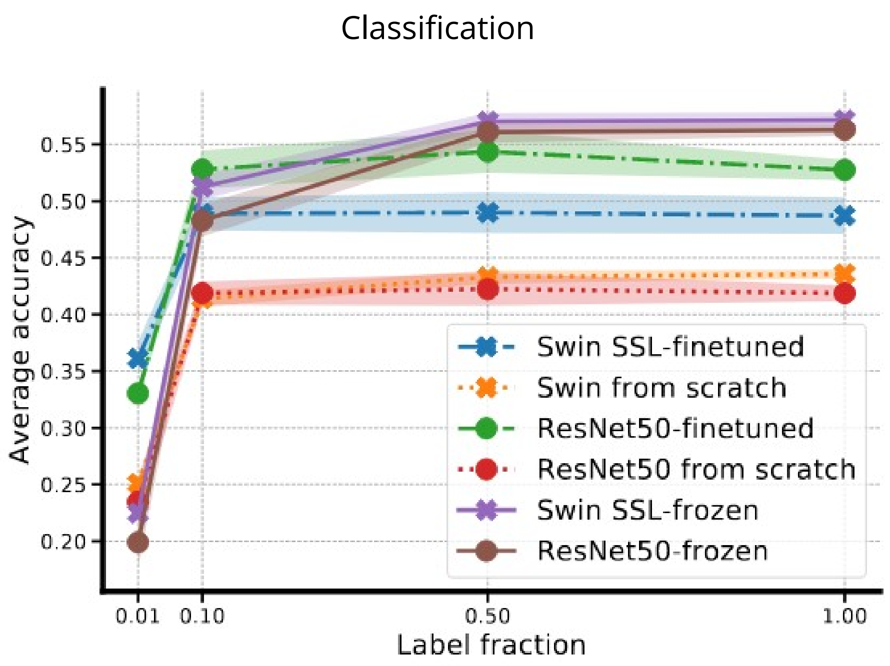

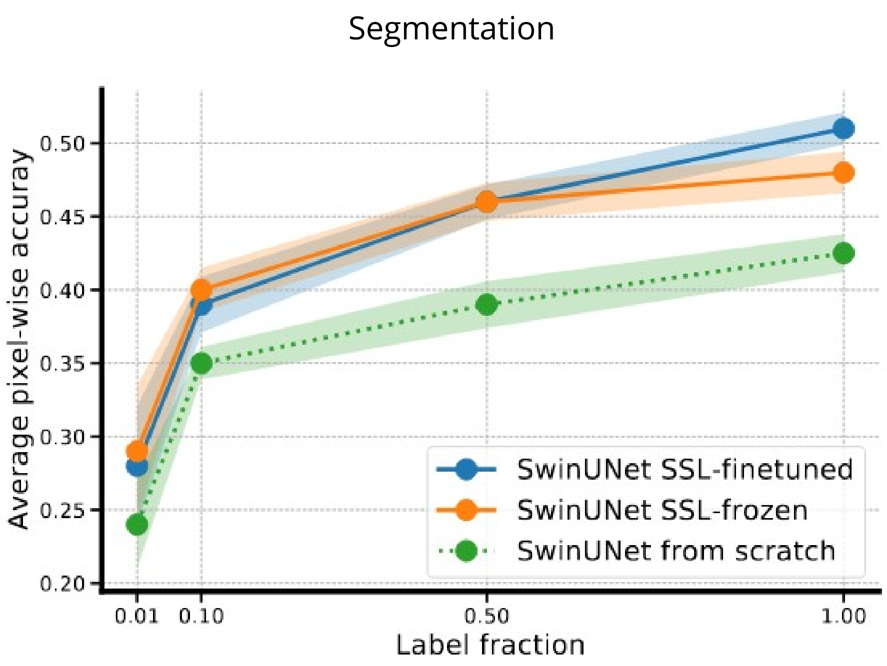

The effect of SSL is **task agnostic** and **architecture agnostic**.

→ SSL pretraining can boost the performance significantly, especially for small datasets!

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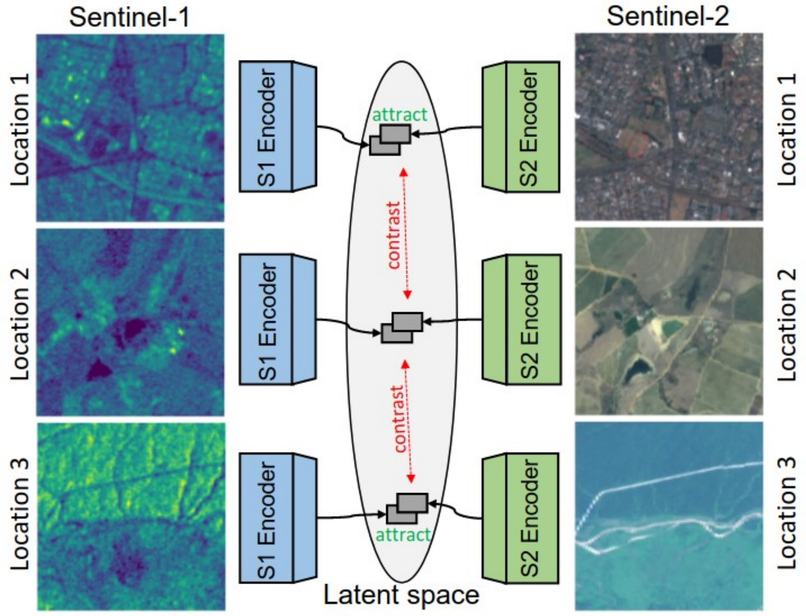
Summary

Self-supervised learning (SSL) improves the data-efficiency of model training by leveraging vast amounts of unannotated data:

- We show that models pre-trained with SSL and fine-tuned on **10% of annotated data** outperform models trained on 100% of annotated data in a fully supervised approach.
- This performance boost is **task-agnostic** and **architecture-agnostic**.



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Self-Supervised Learning for Earth Observation: Leveraging a wealth of multi-modal data

SWISS NATIONAL SCIENCE FOUNDATION

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BEN-GE: EXTENDING BIGEARTHNET WITH GEOGRAPHICAL AND ENVIRONMENTAL DATA

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(1): School of Computer Science, Universität St. Gallen; (2): Technische Universität Berlin

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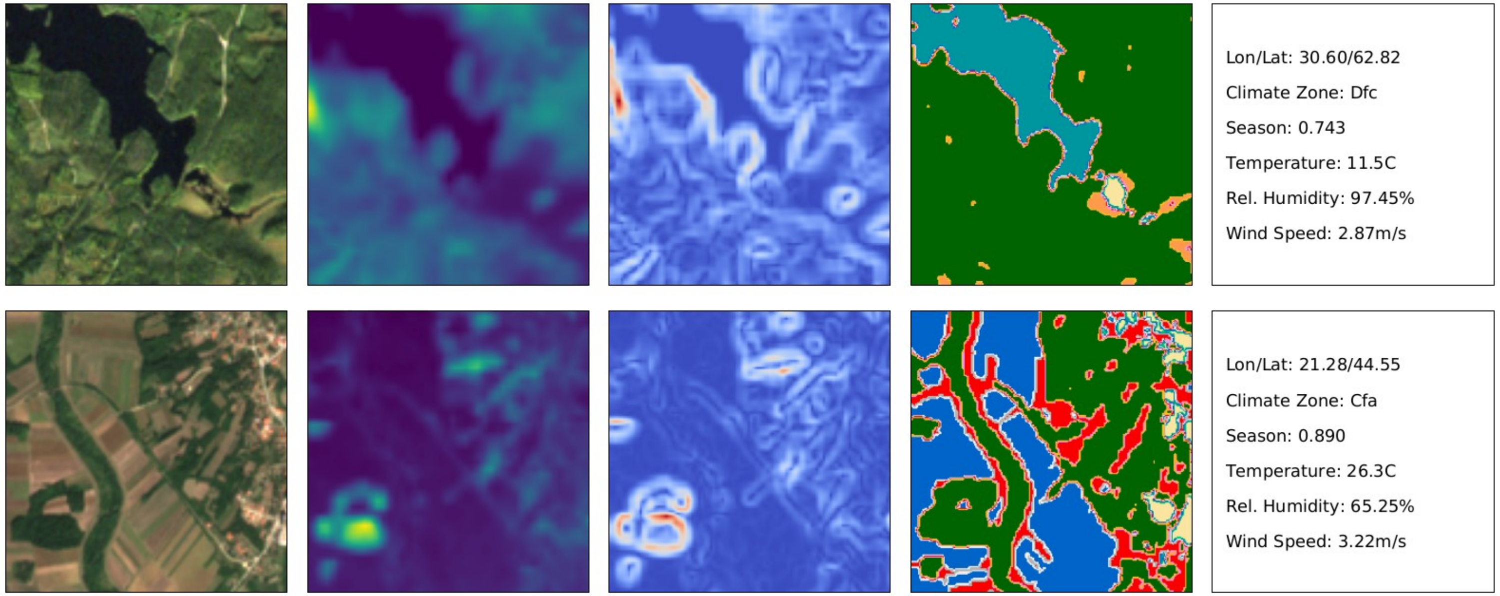

Elevation Slope + Az Land-use Environmental x **590,326** tiles

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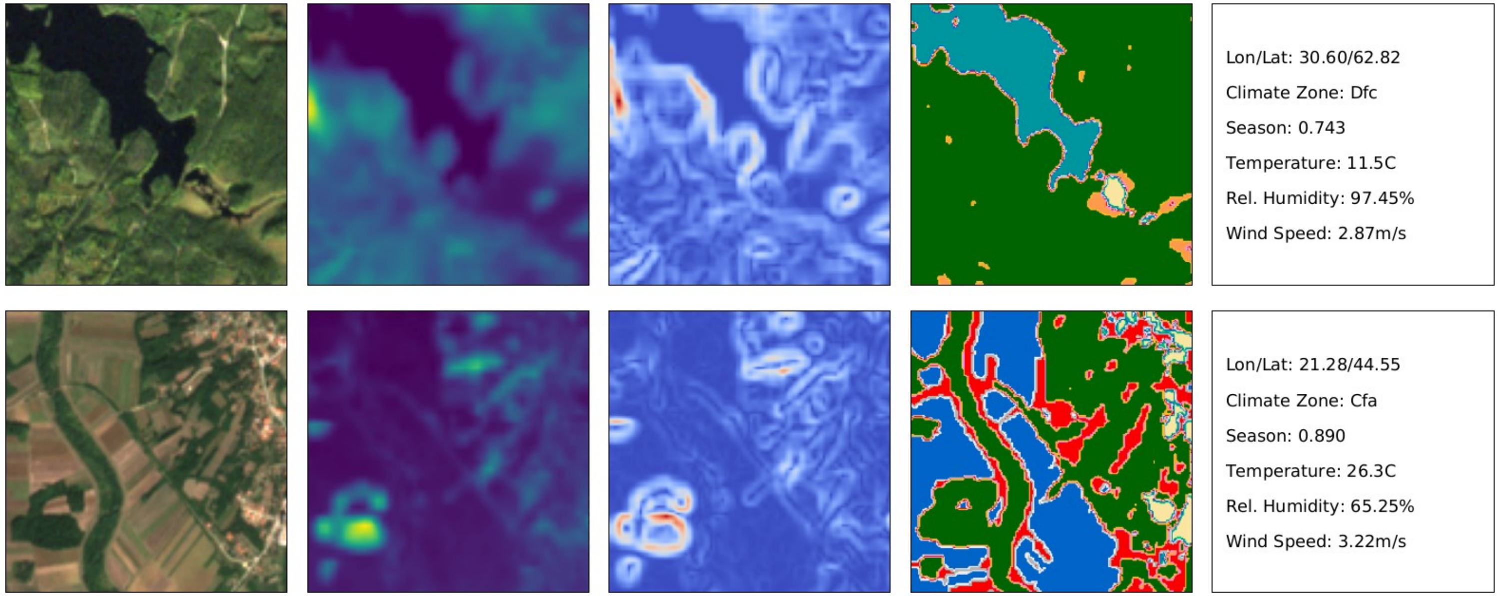
Stay tuned!



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