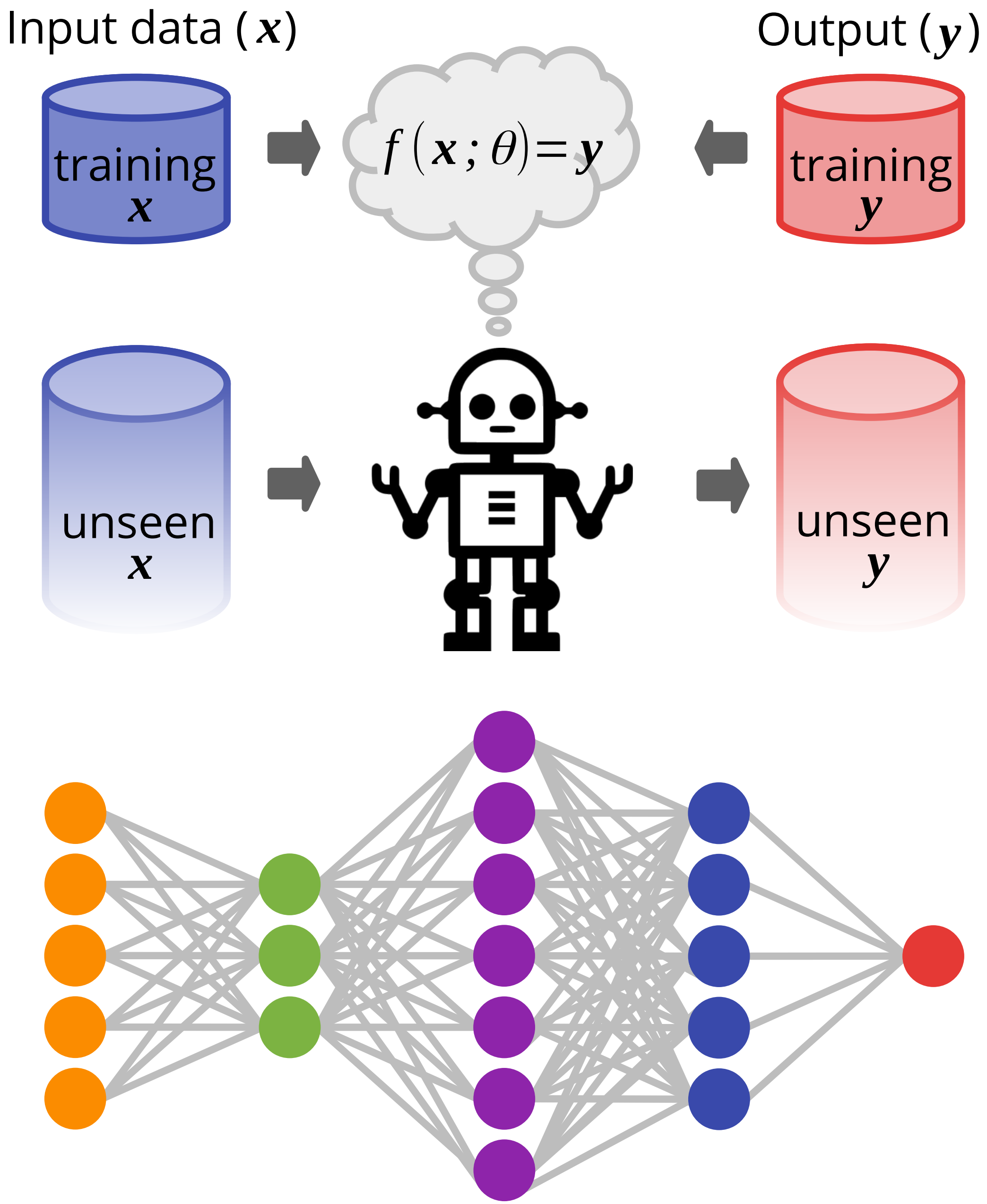
Label-efficient Deep Learning in Remote Sensing

Michael Mommert, University of St. Gallen

Resources: github.com/mommermi/iadfschool2023_efficientlearning

Introduction



Deep Learning for Earth observation

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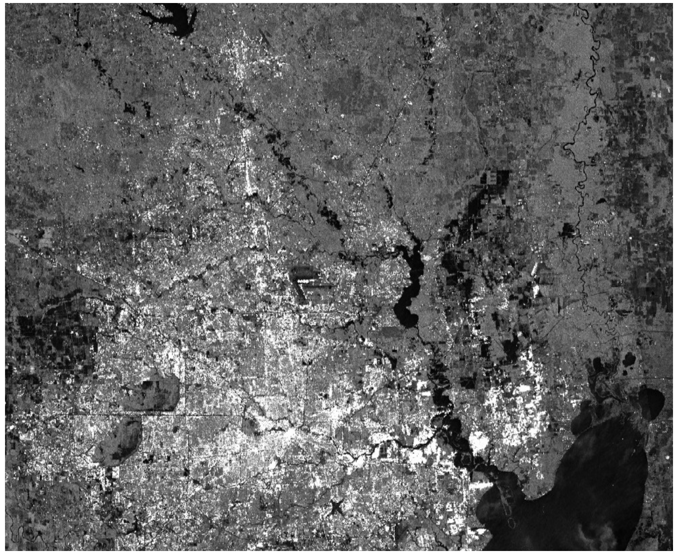
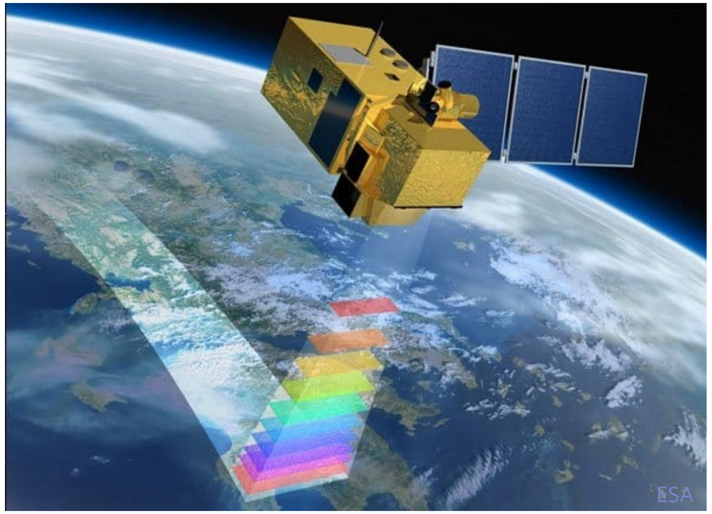
Earth observation data are highly complex (unstructured, multi-modal).





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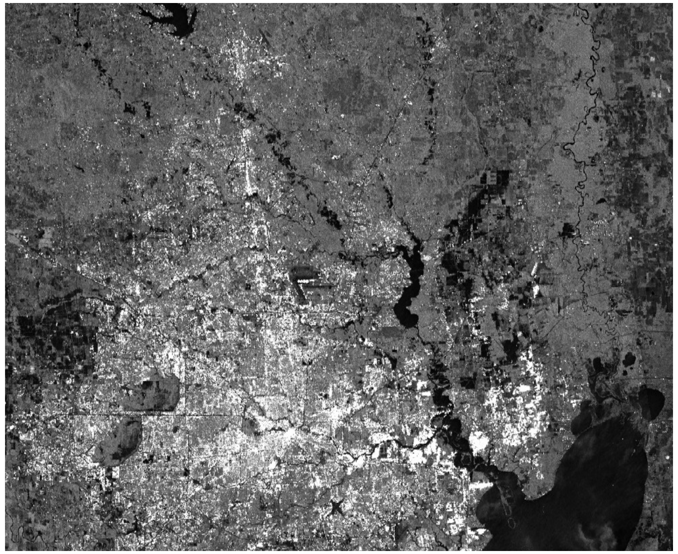

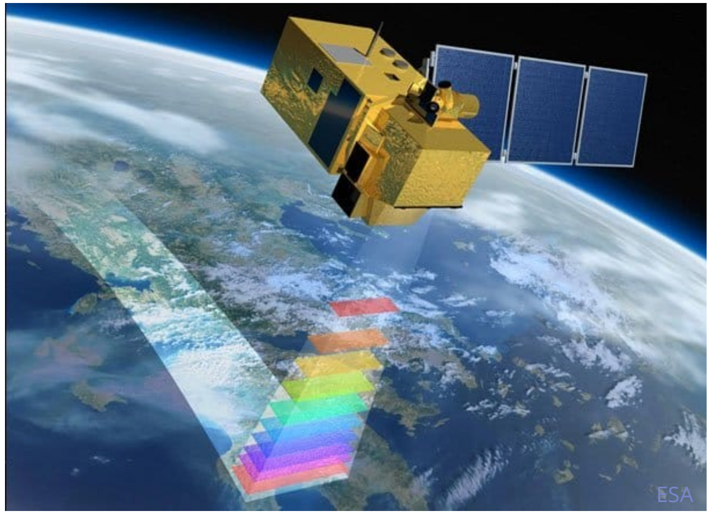

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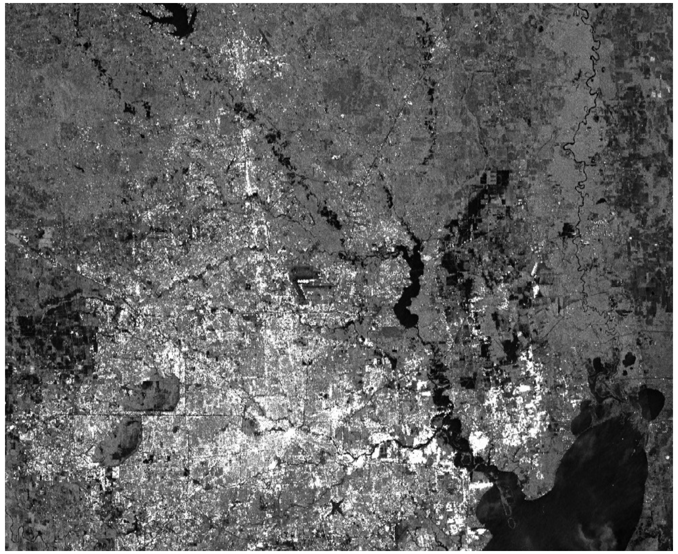

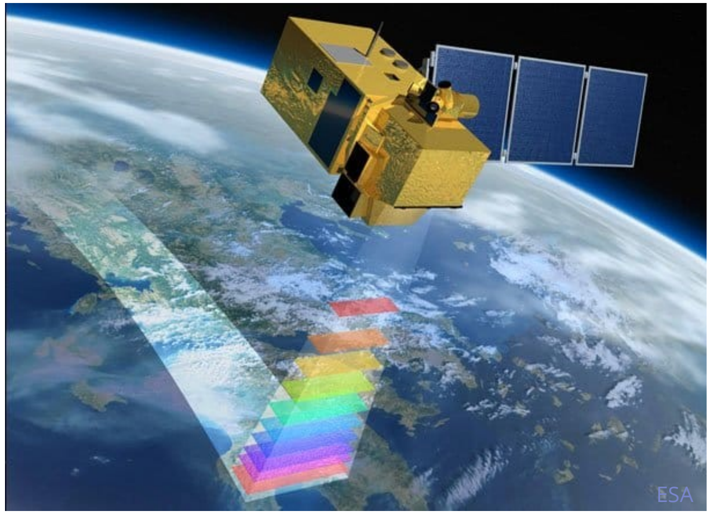

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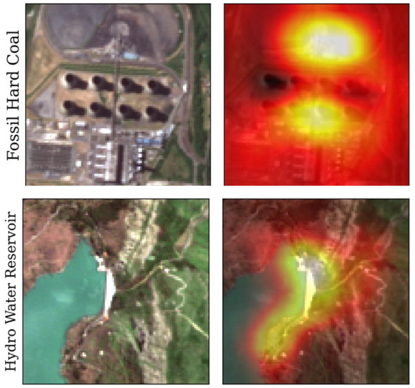
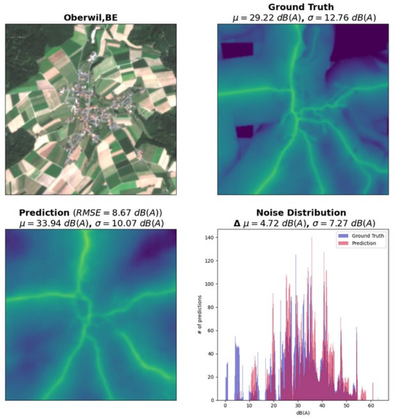
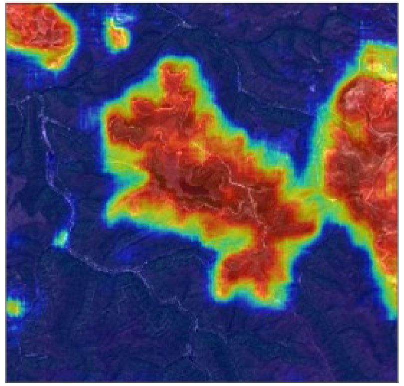
Deep Learning also offers the **flexibility** to deal with a range of different tasks.



Classification



Regression



Segmentation

Object Detection

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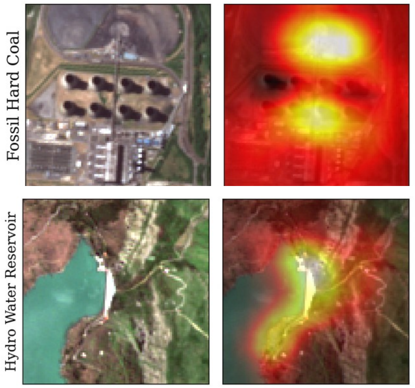
How does it work?



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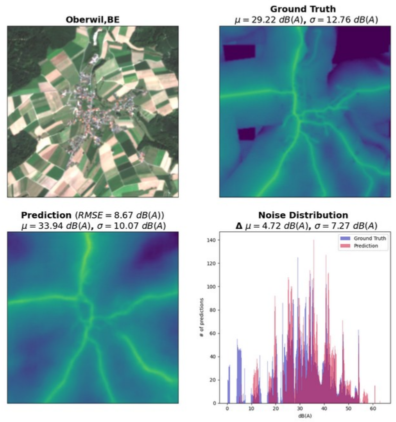

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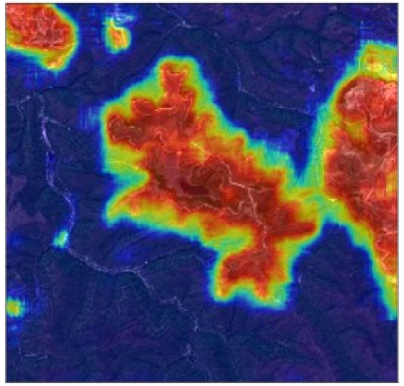

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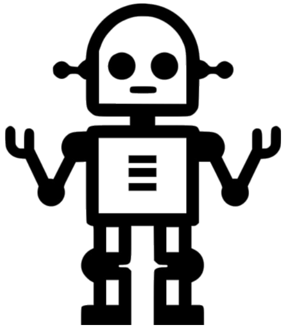
Supervised learning with Neural Networks



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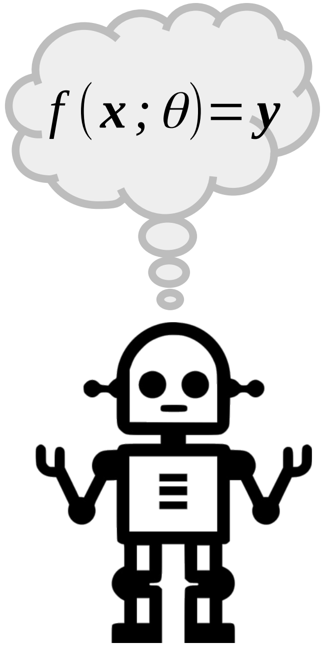

A machine learns a task from **annotated examples**.

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

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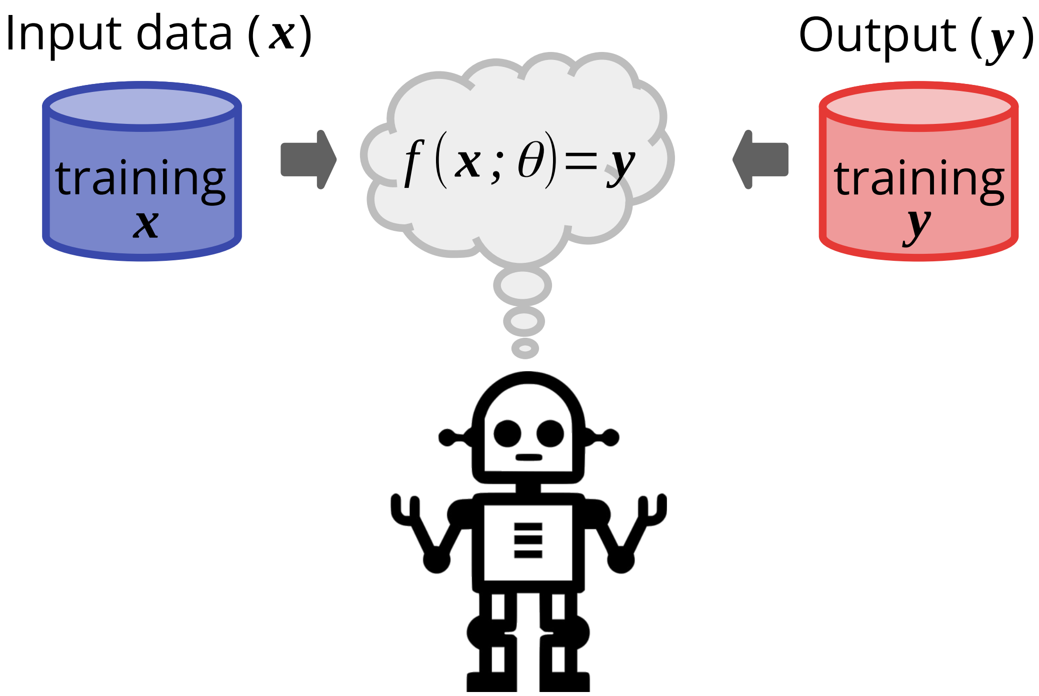

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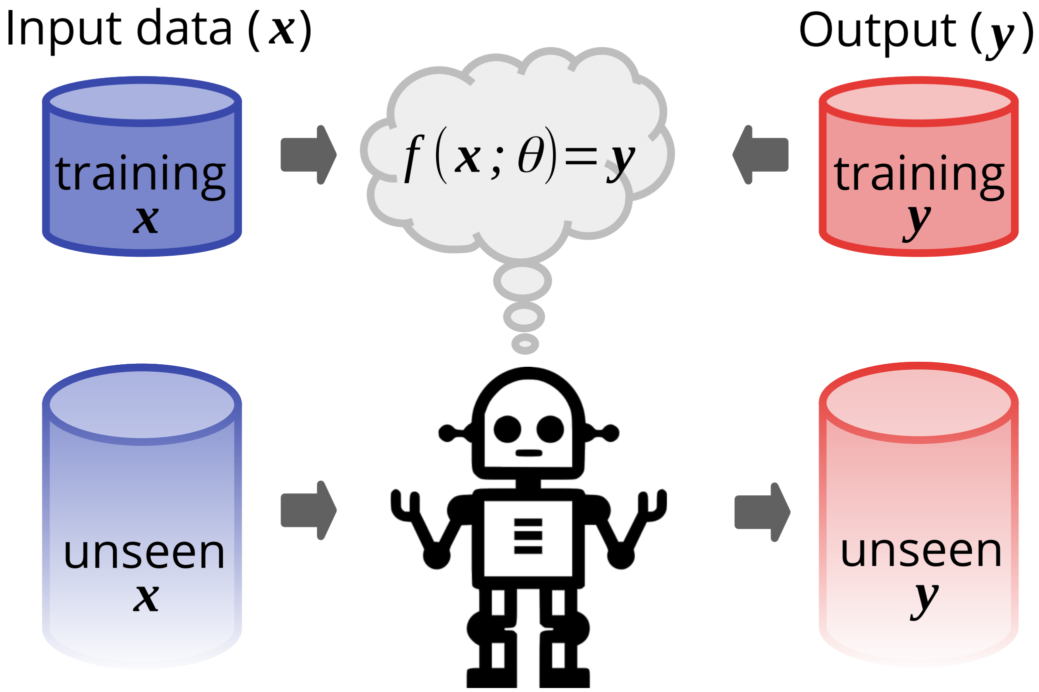

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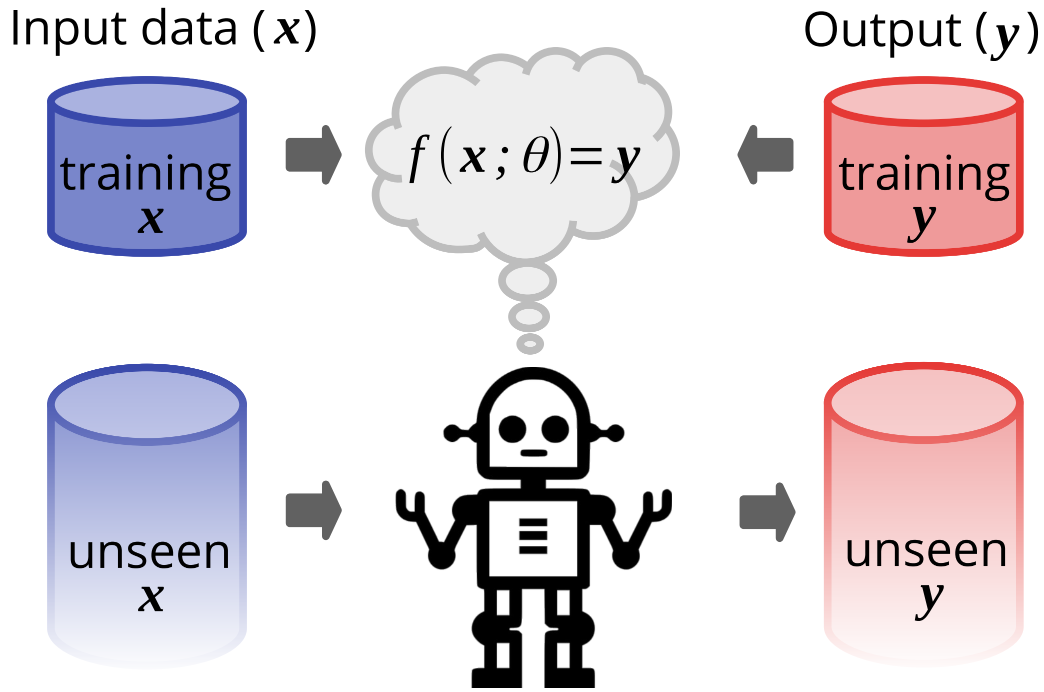

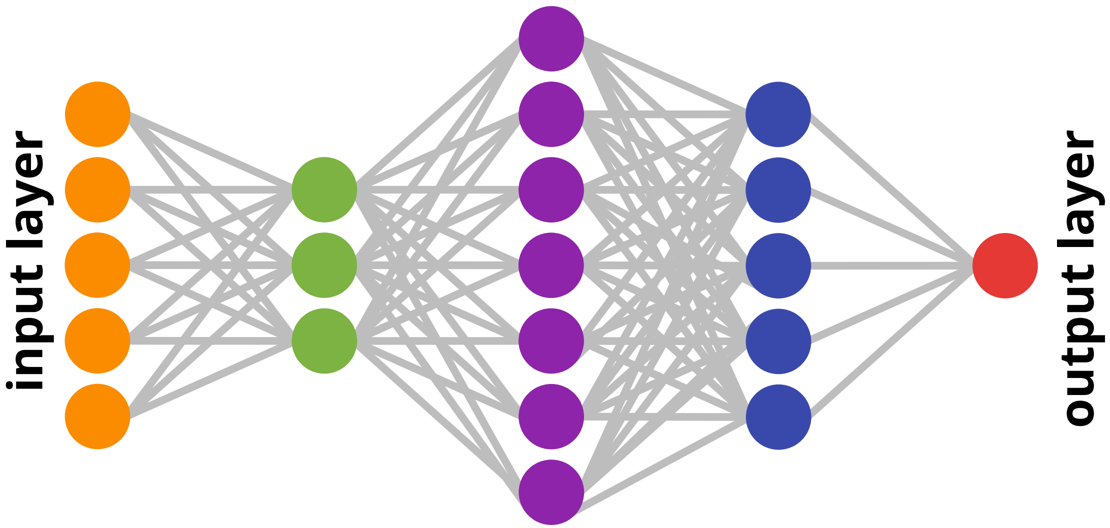

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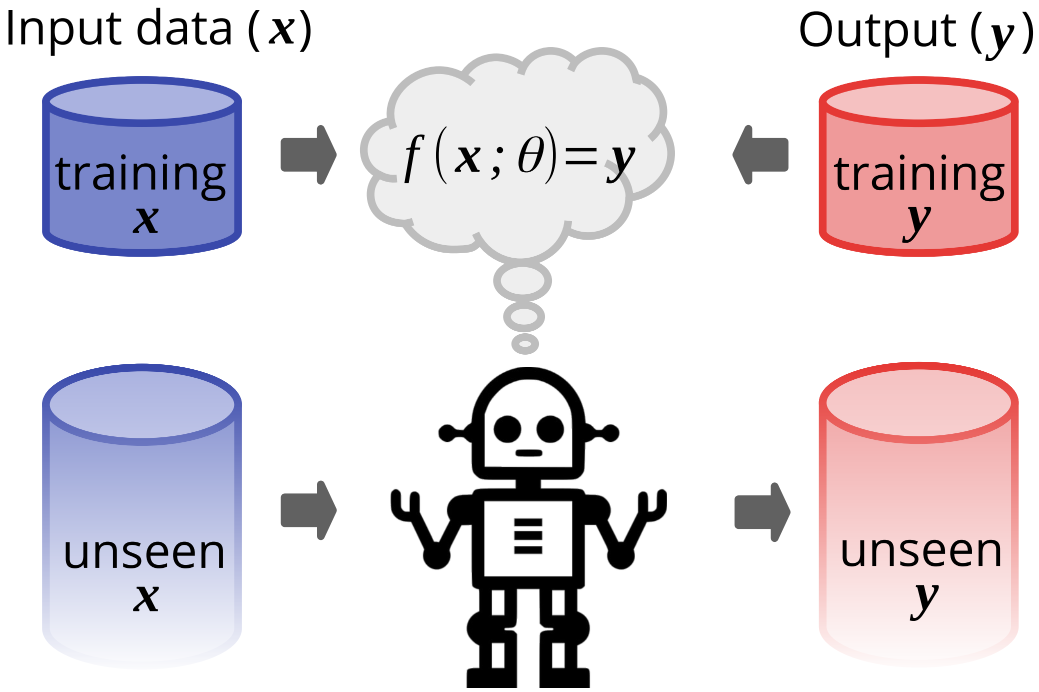

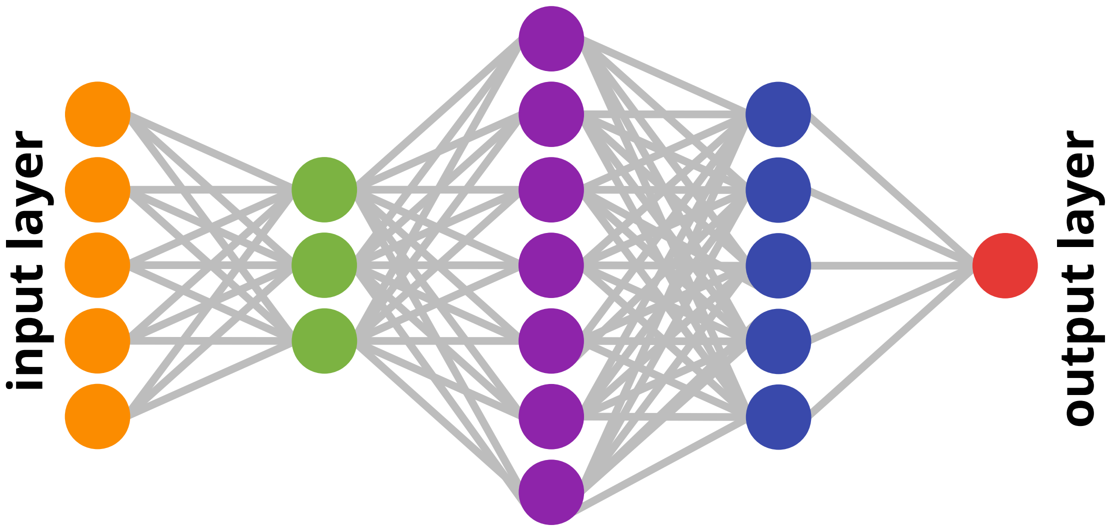

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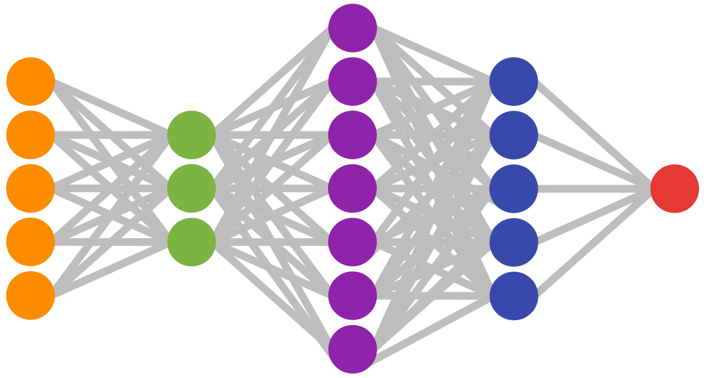
How does the model learn?

Neural network training pipeline



Neural network training pipeline

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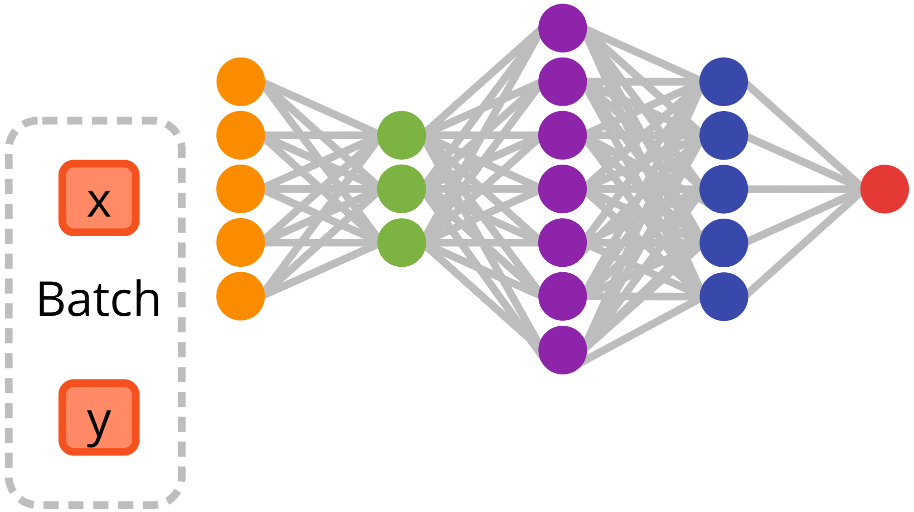

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- Sample batch (input data x and target data y) from training dataset:
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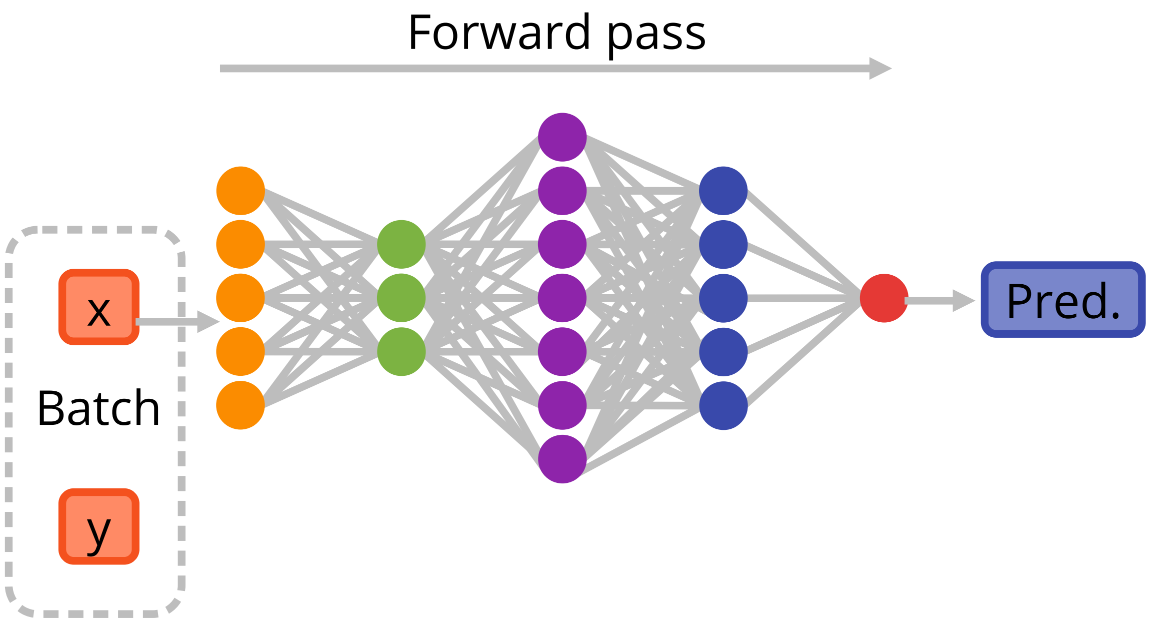

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- Sample batch (input data x and target data y) from training dataset:
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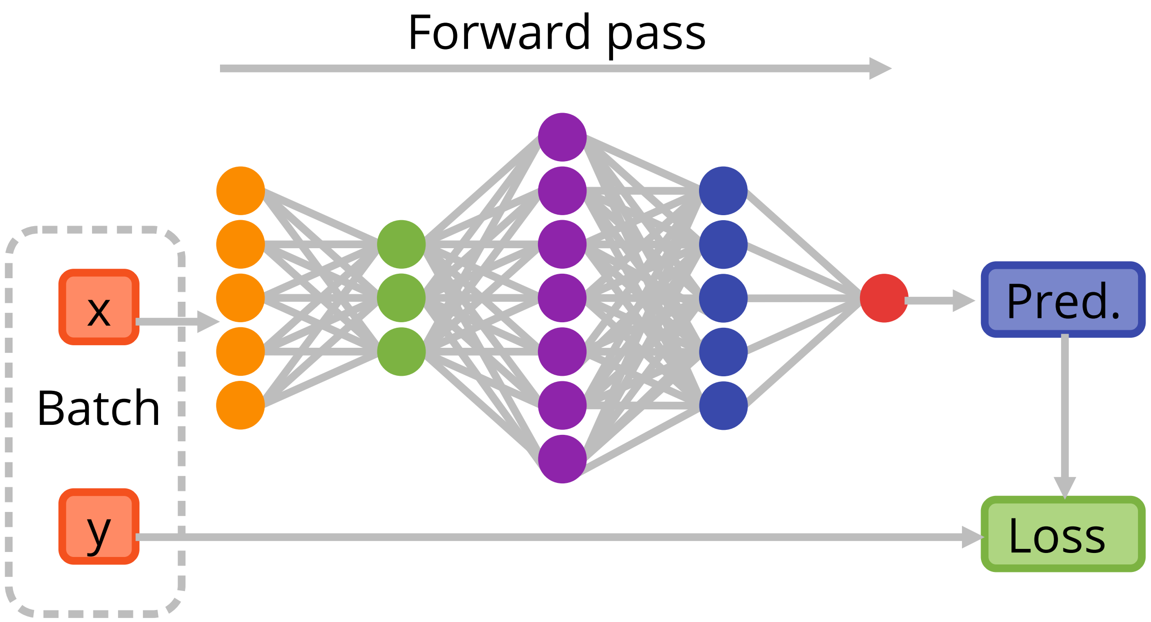

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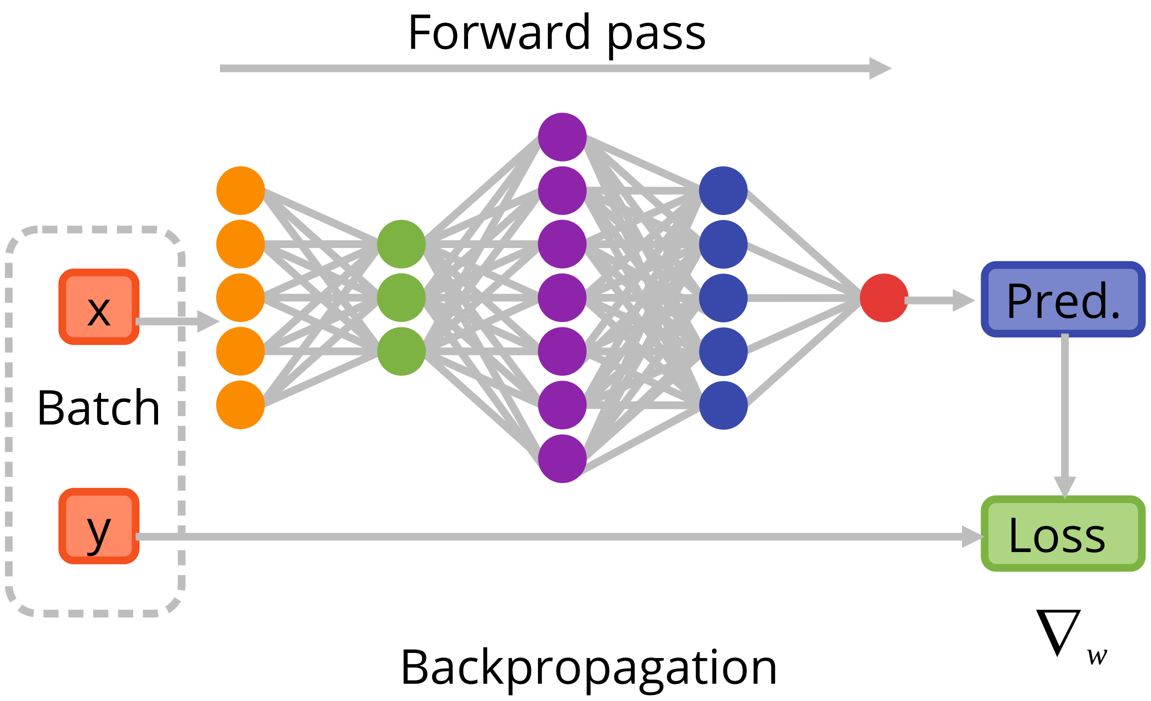

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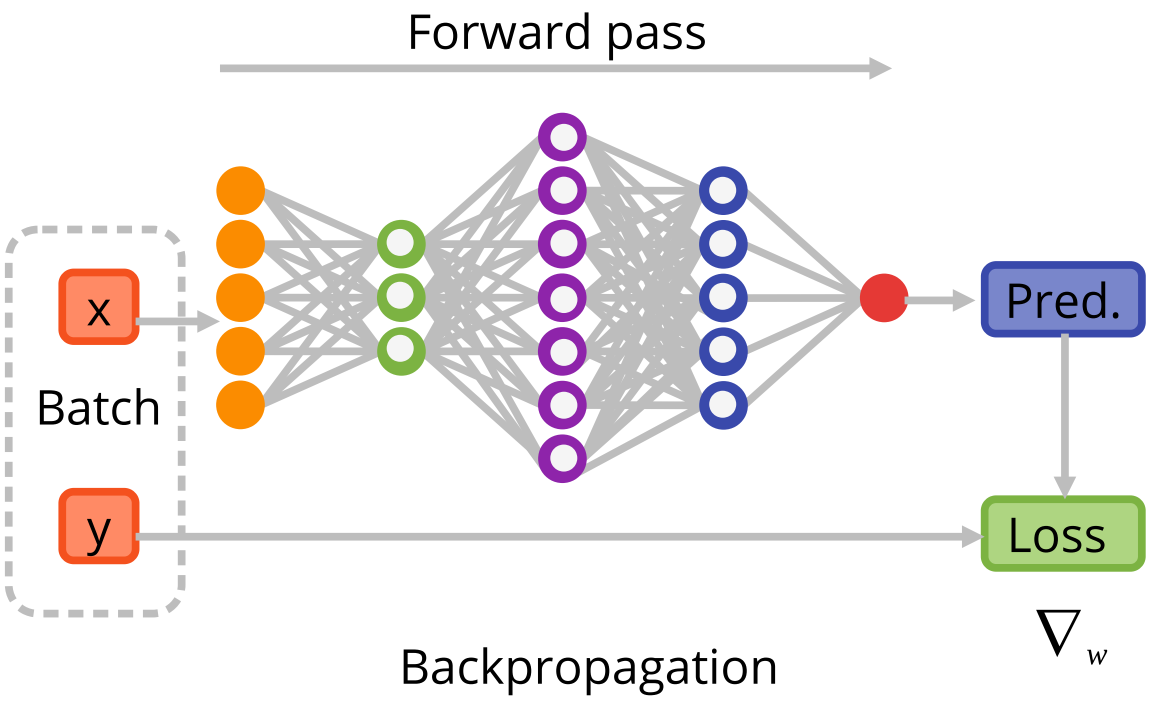

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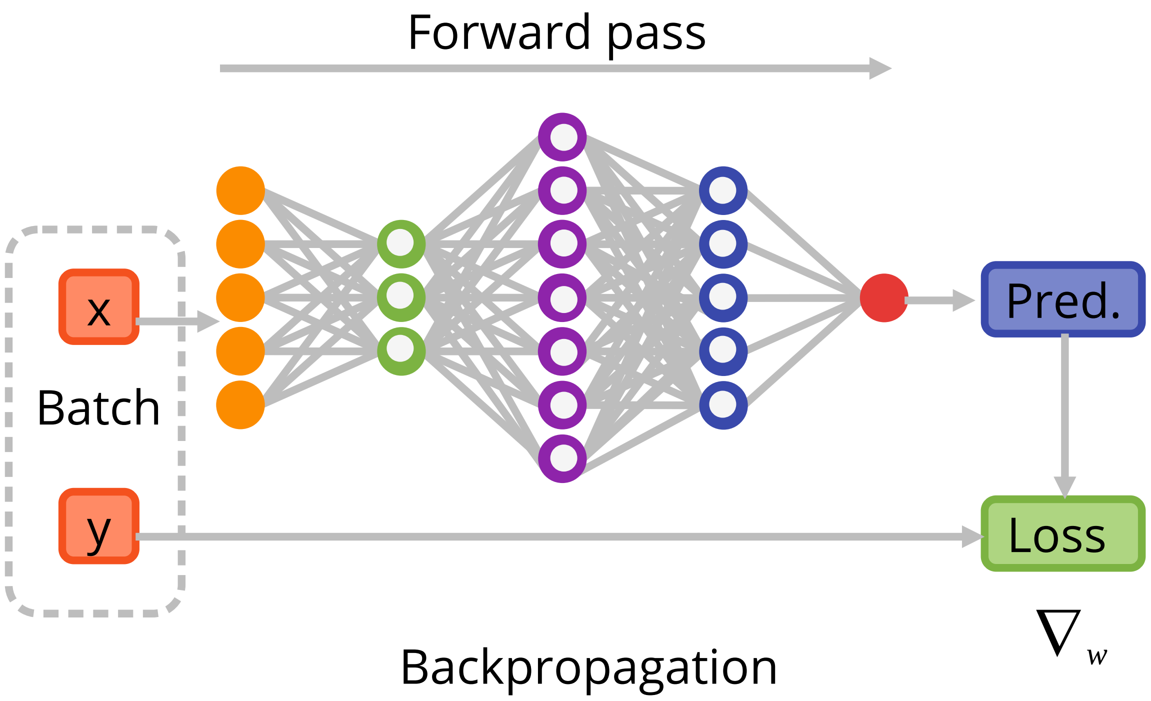

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- Sample batch (input data x and target data y) from training dataset:

1 epoch

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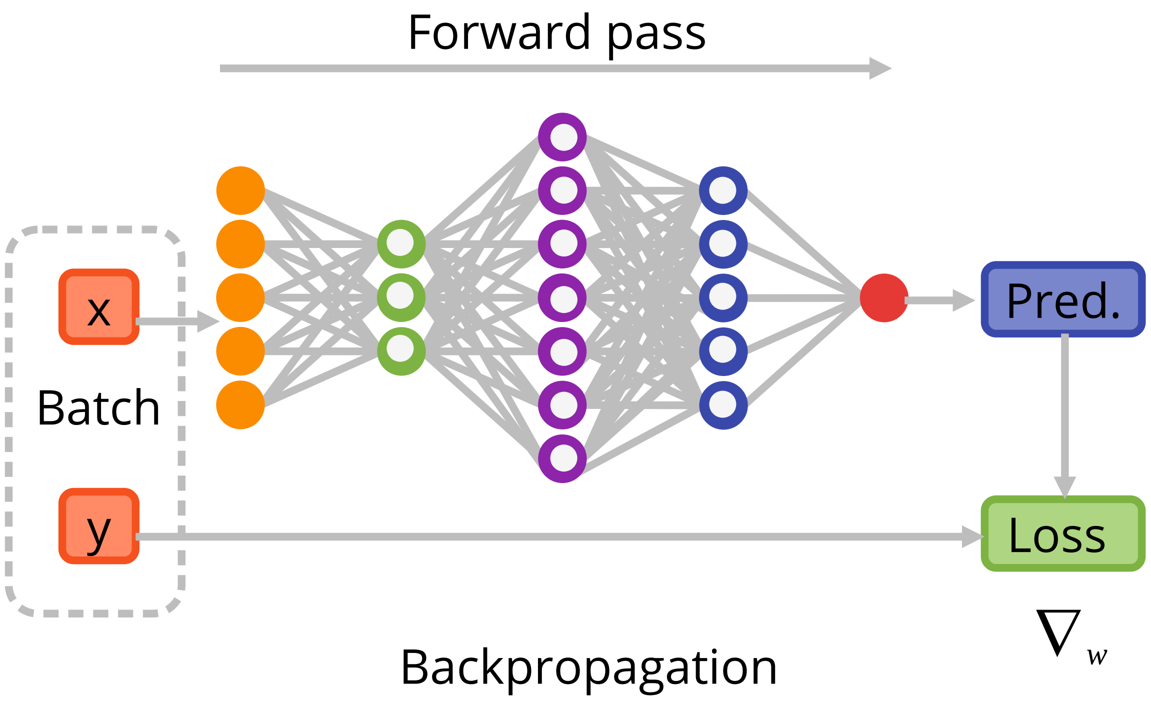

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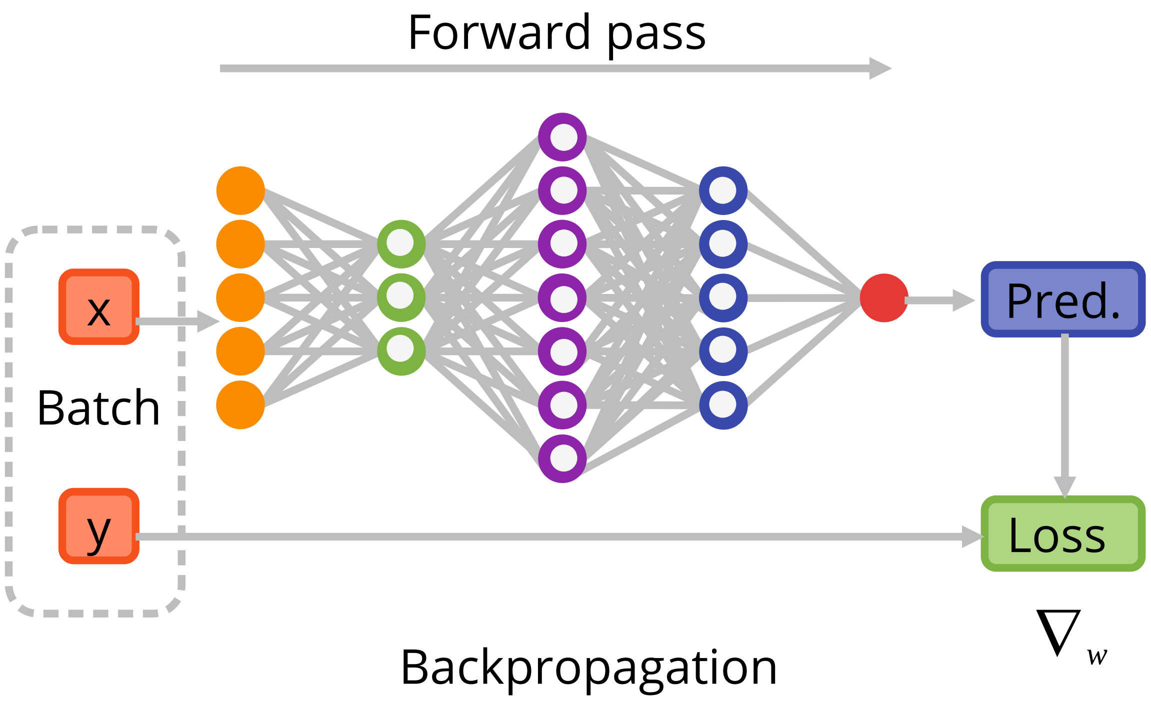
- Stop before overfitting sets in



Let's implement a fully supervised learning pipeline with PyTorch and PyTorch Lightning!

Please go to:

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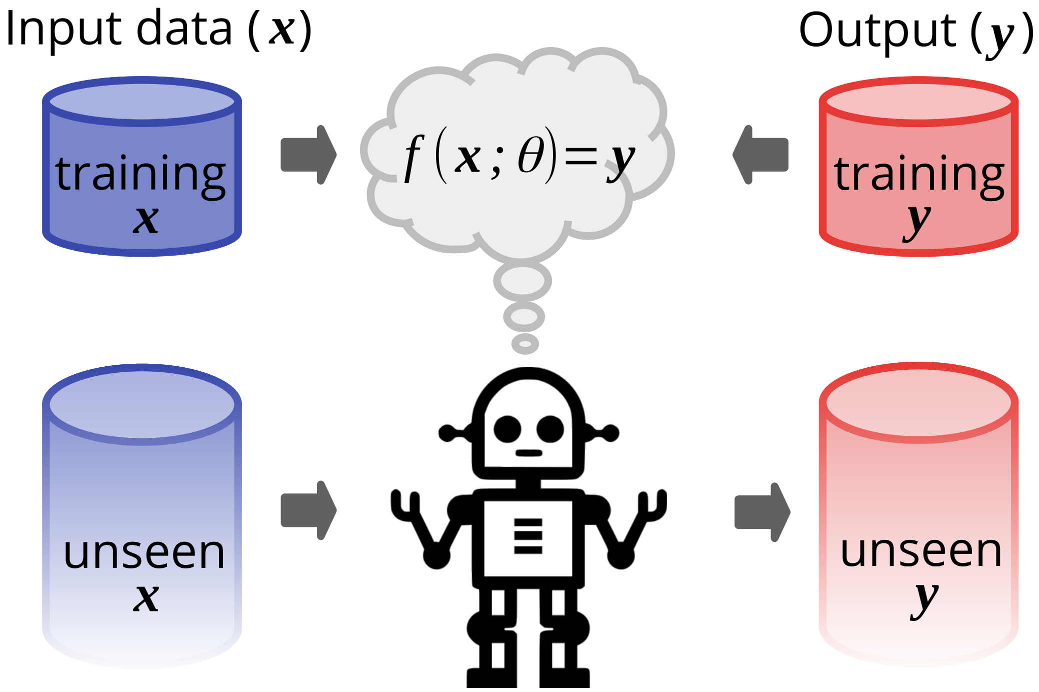

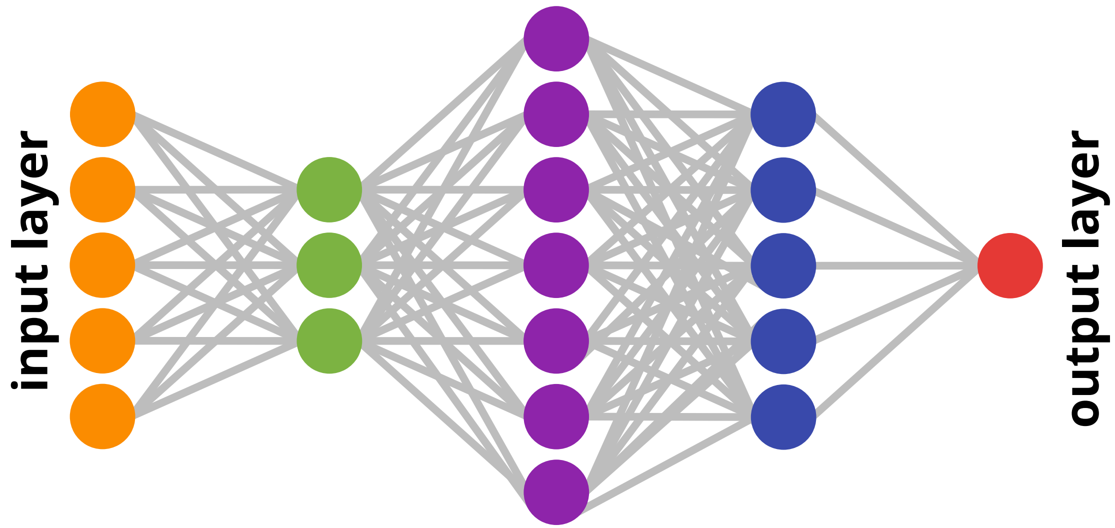

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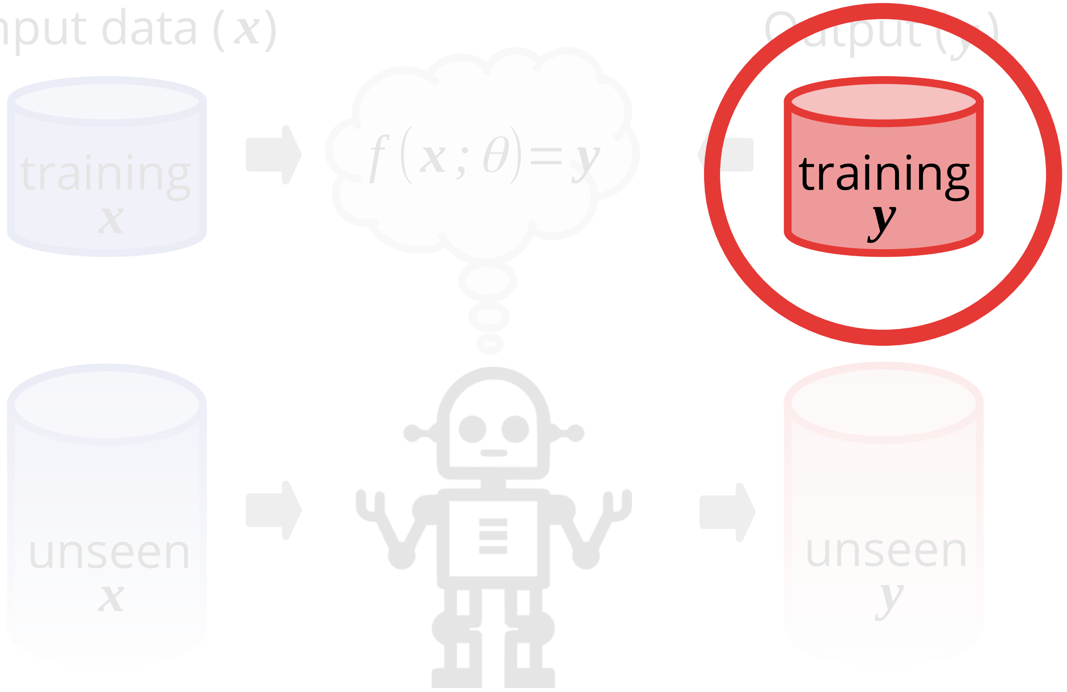
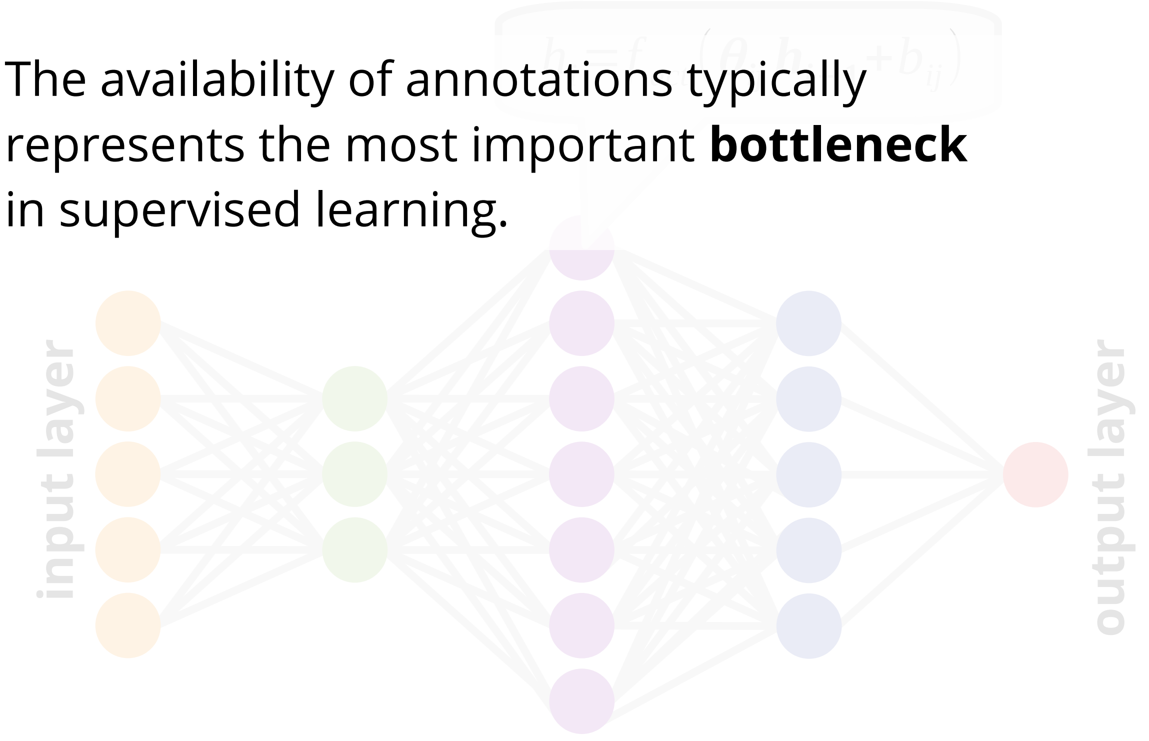


The availability of annotations typically represents the most important **bottleneck** in supervised learning.



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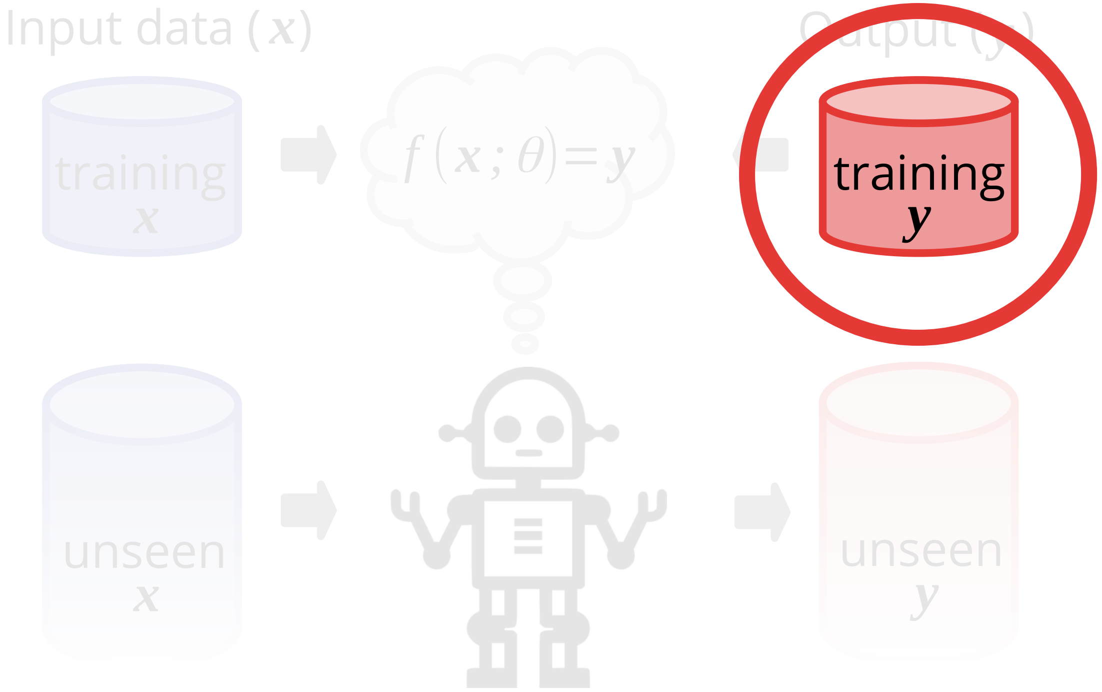

The availability of annotations typically represents the most important **bottleneck** in supervised learning.

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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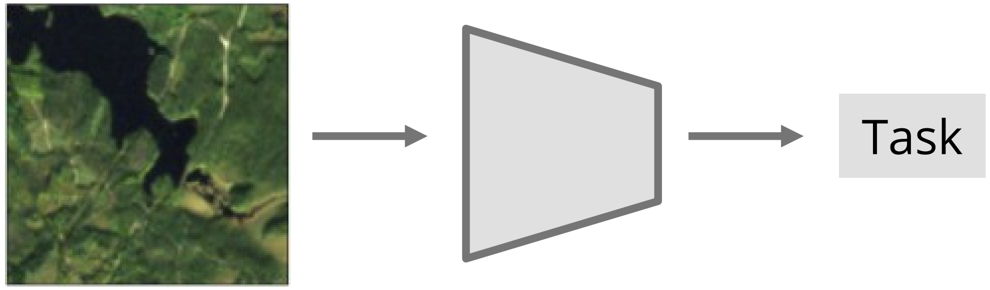

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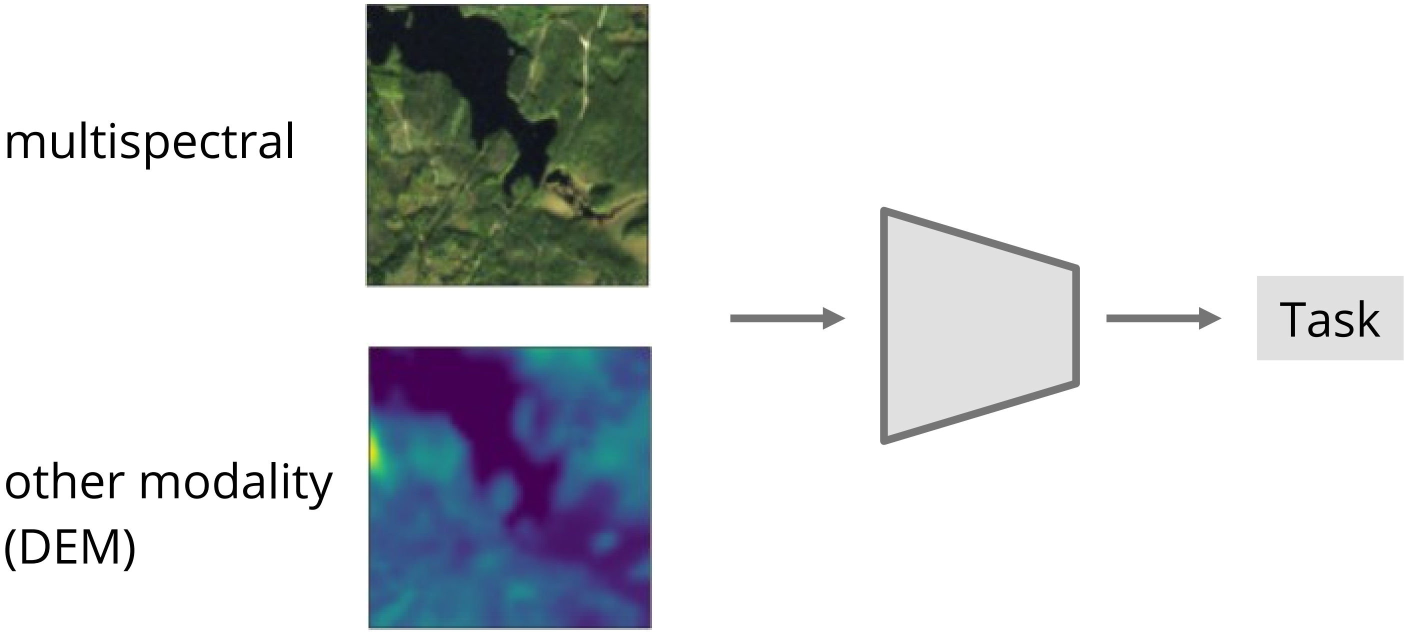

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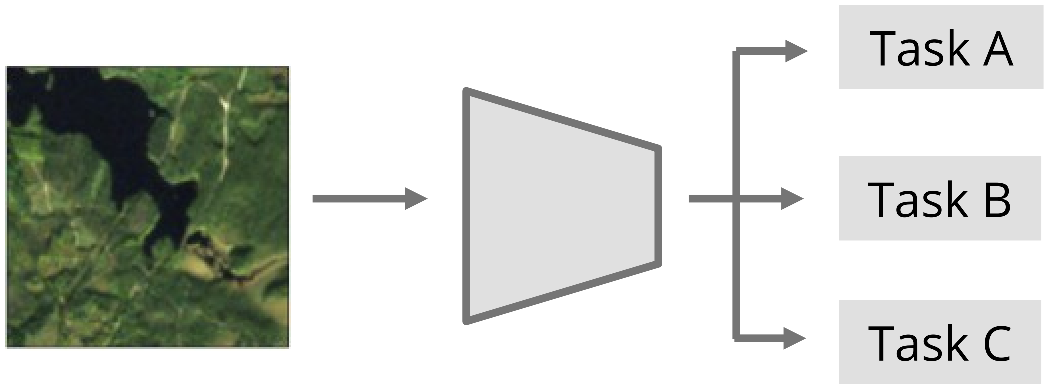

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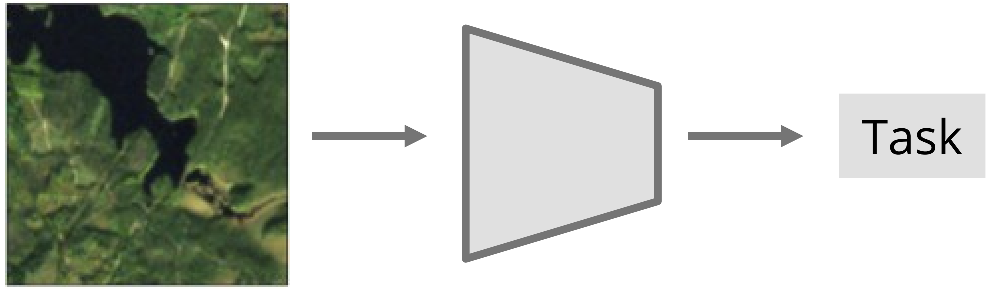

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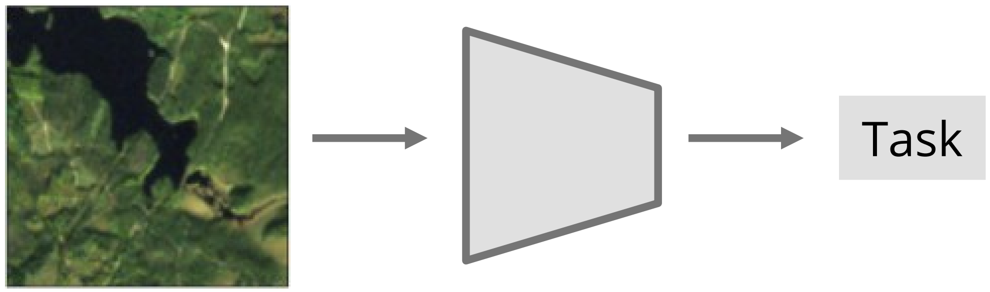

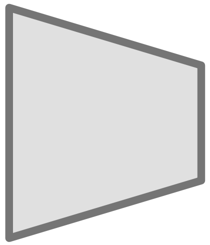

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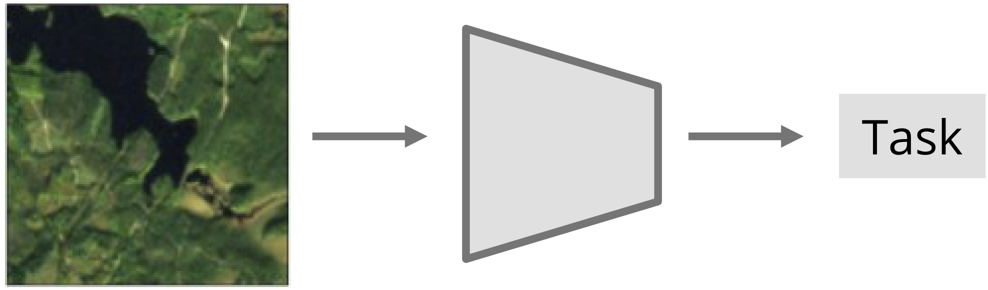
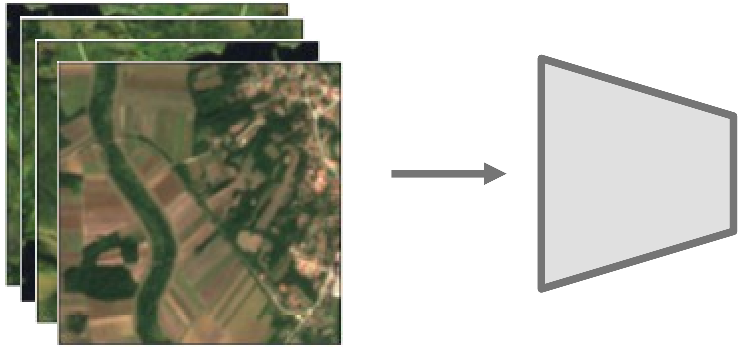


other dataset



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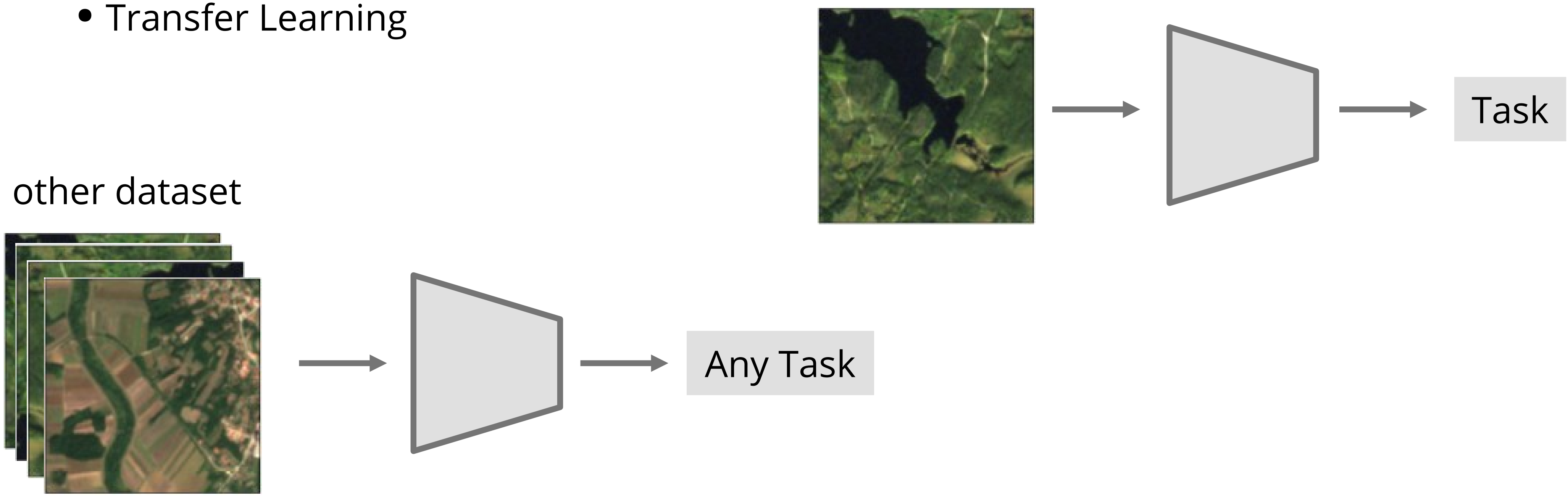

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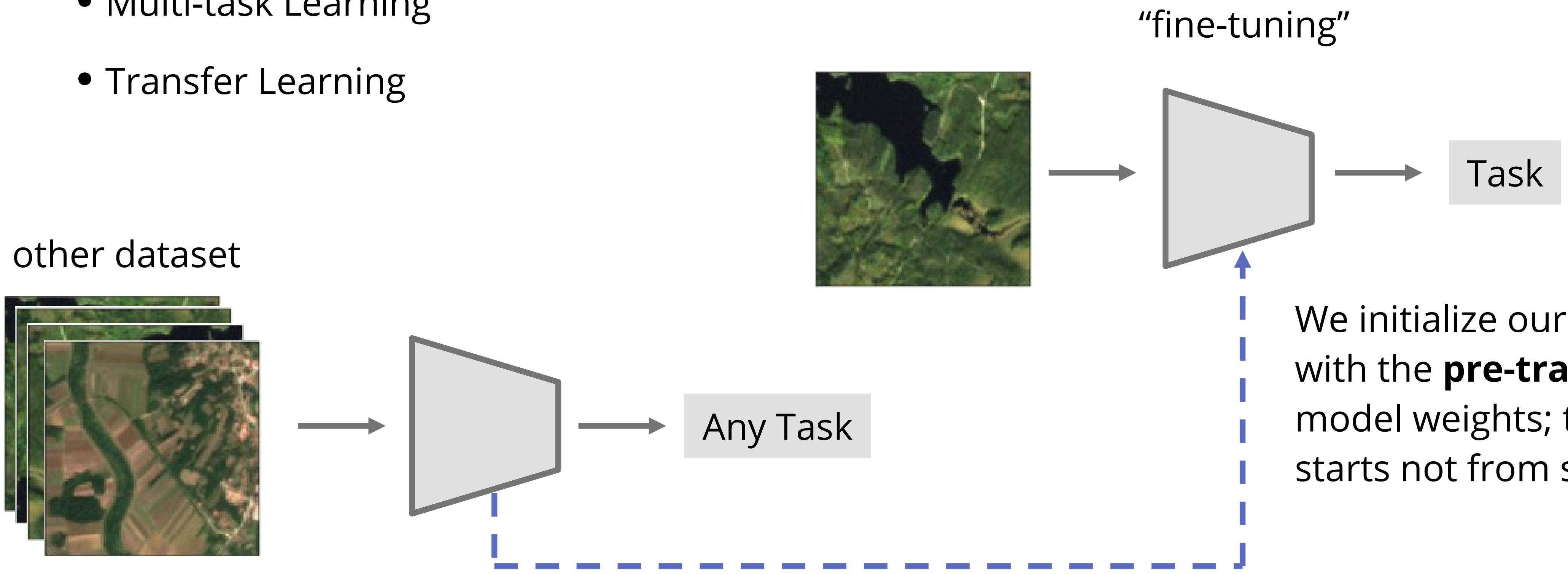

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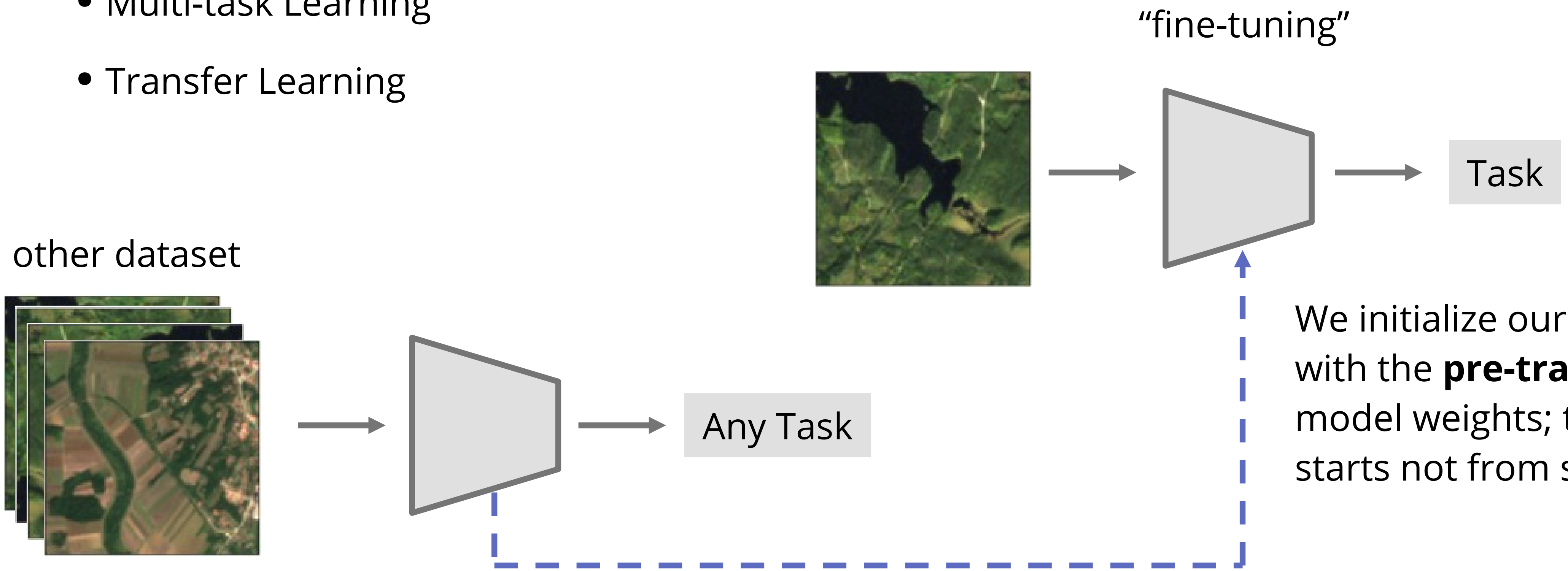

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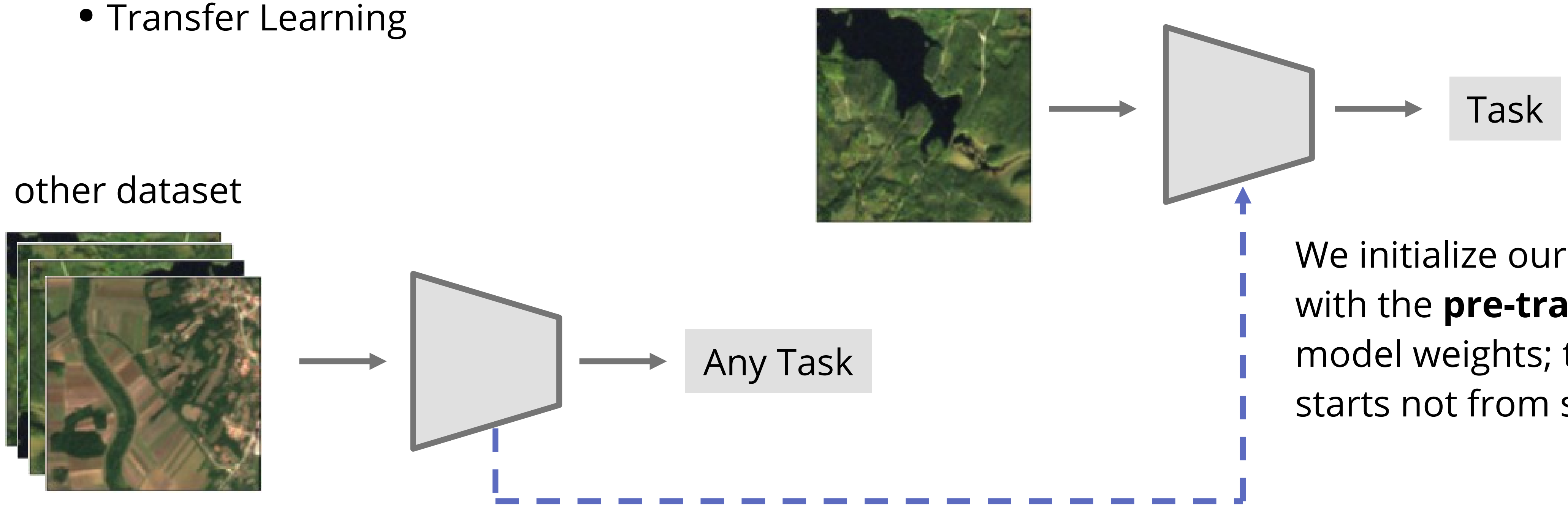
Can we pretrain a model from unannotated data?

“fine-tuning”



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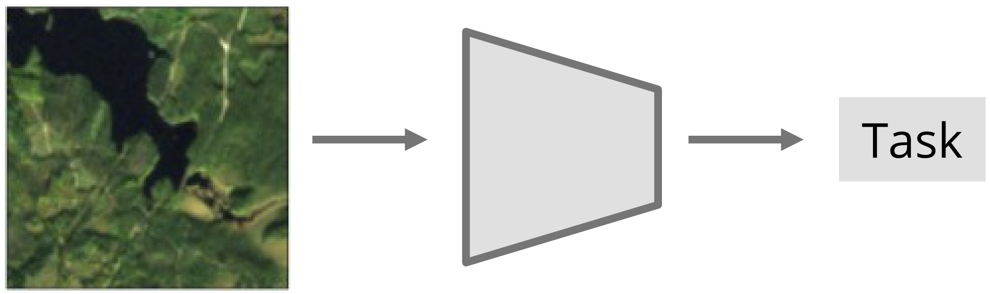

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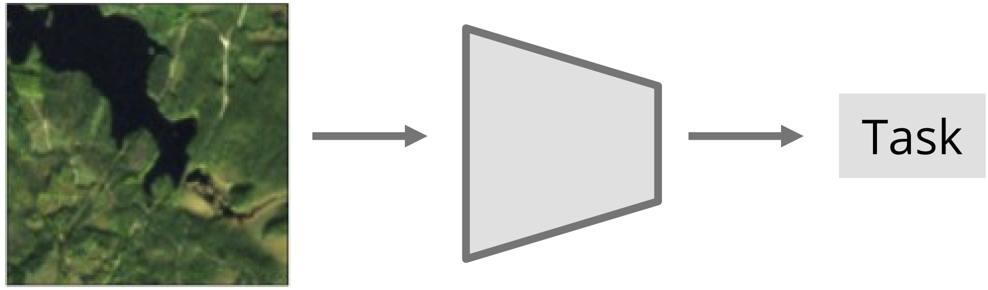

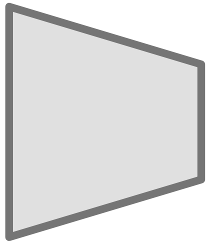

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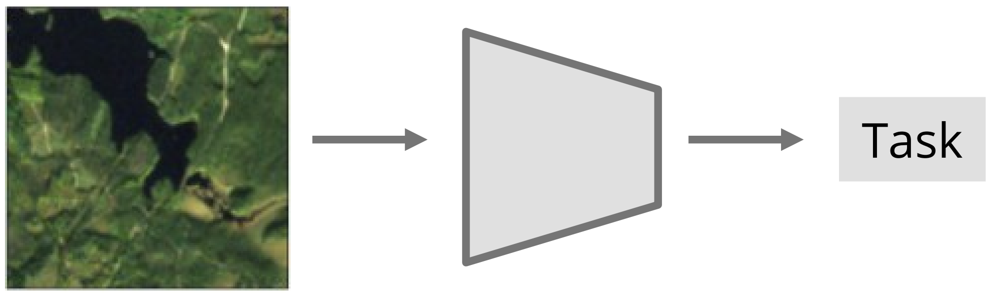

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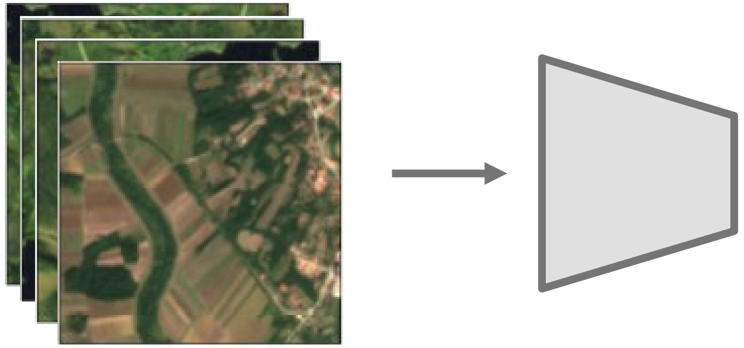

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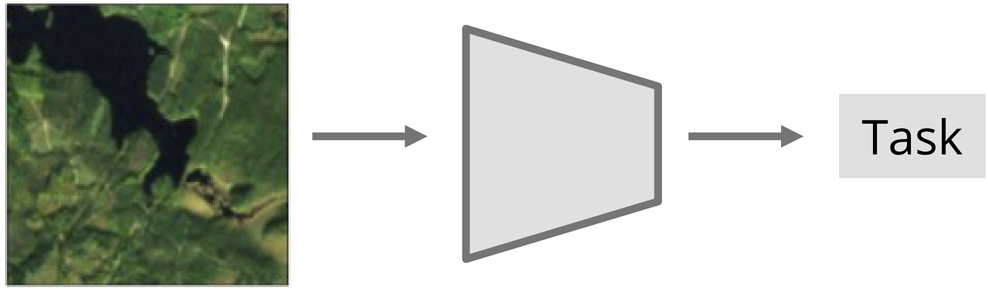

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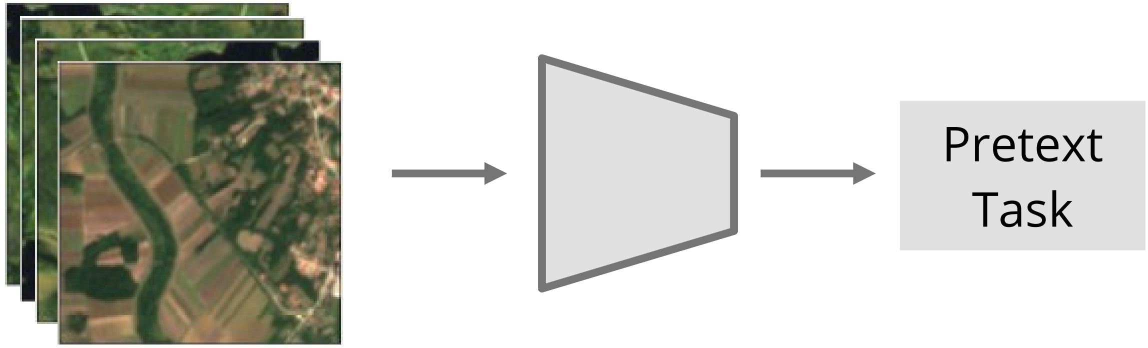

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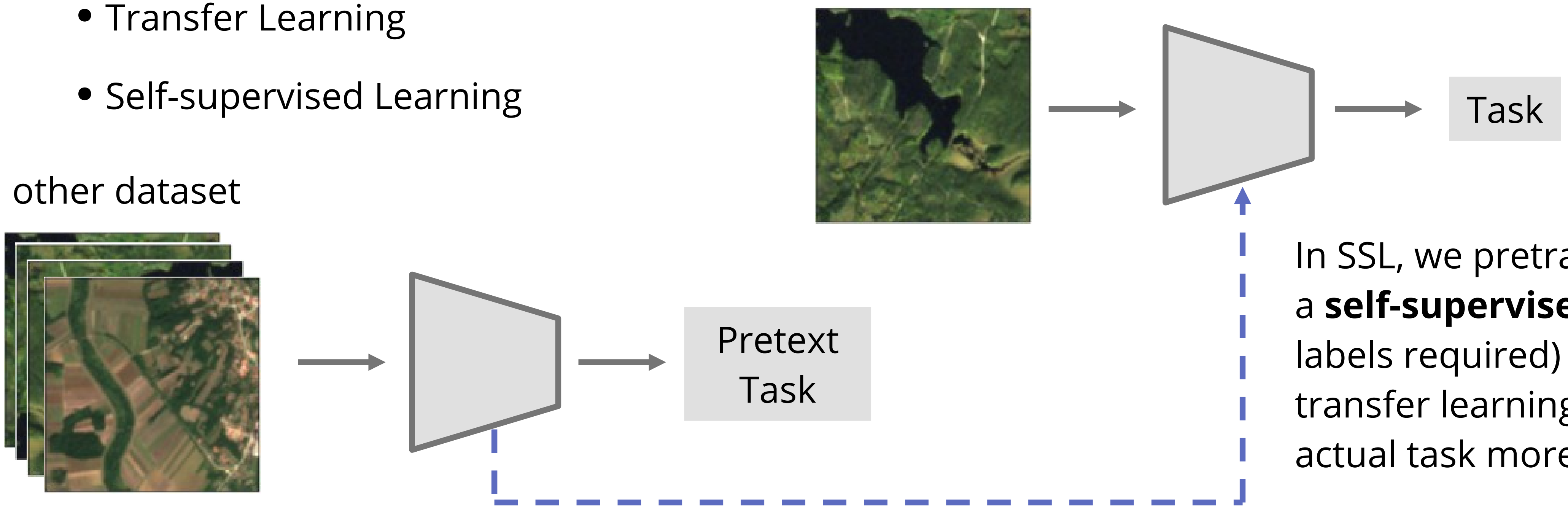

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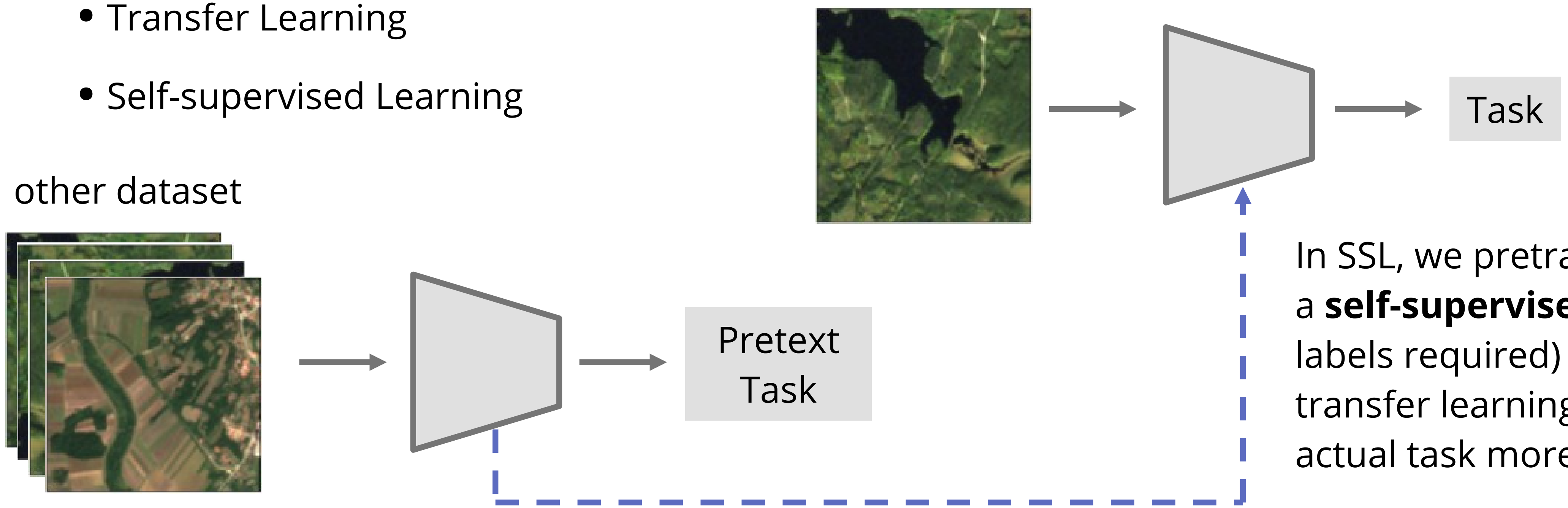

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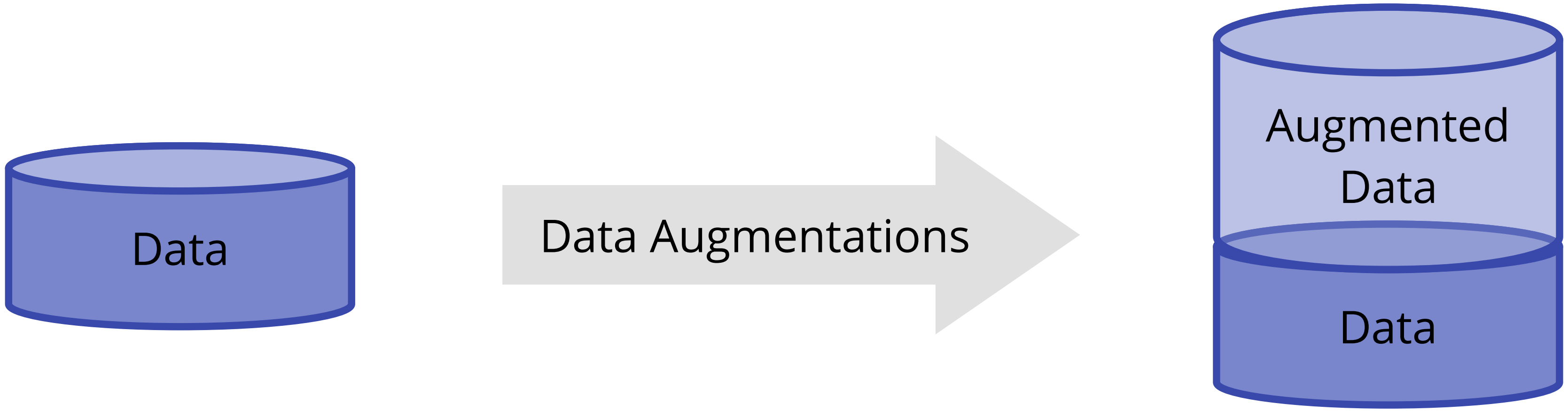
- Multi-task Learning
- Transfer Learning
- Self-supervised Learning

We will introduce these methods in the following and implement some them using PyTorch after the coffee break.

Data Augmentations

Data Augmentations

Data augmentations are a means to synthetically “increase the size” of your dataset. Augmentations are **transformations** that affect input data but not the corresponding labels; as a result, models trained with data augmentations tend to be **more robust** and **less prone to overfitting**.



Data Augmentations in Computer Vision

Original

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Flip

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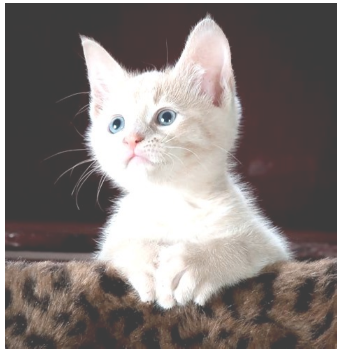

Image
Enhancements

Data Augmentations in Computer Vision

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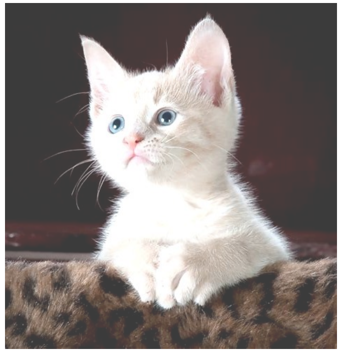

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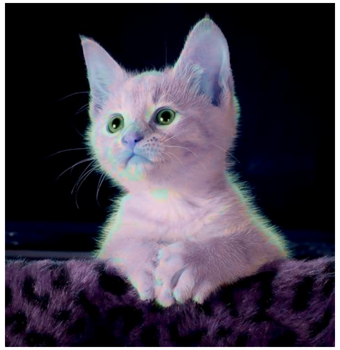

Color
distortions

Data Augmentations in Computer Vision

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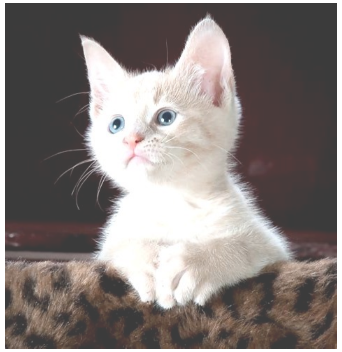

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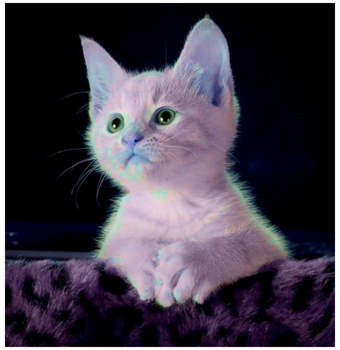

Color
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Crop

Data Augmentations for Remote Imaging Data

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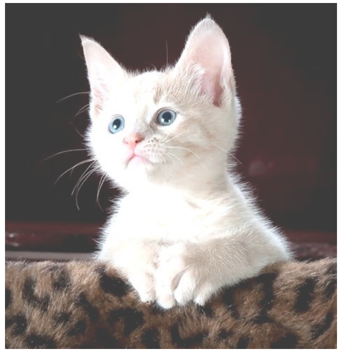
Flip



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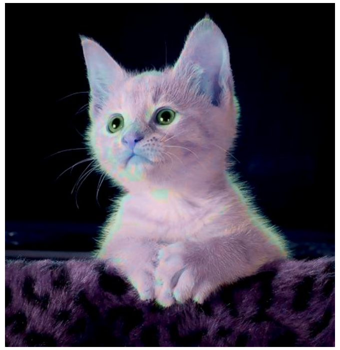

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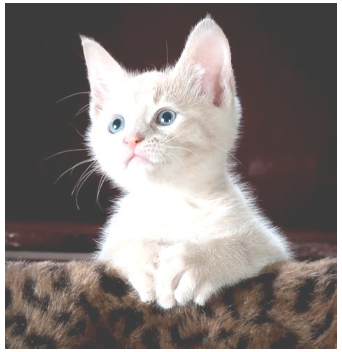

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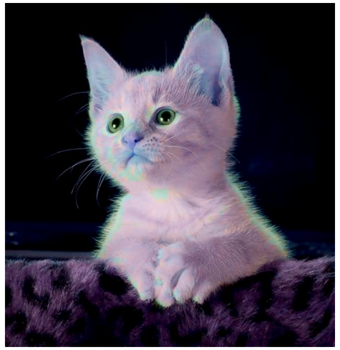

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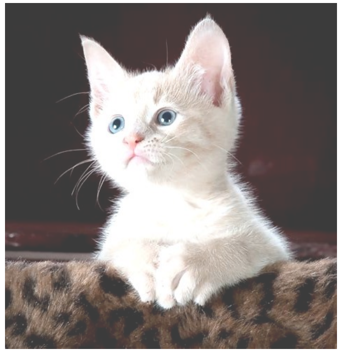

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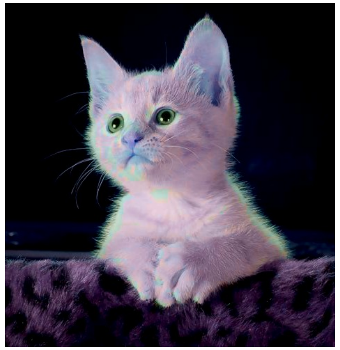

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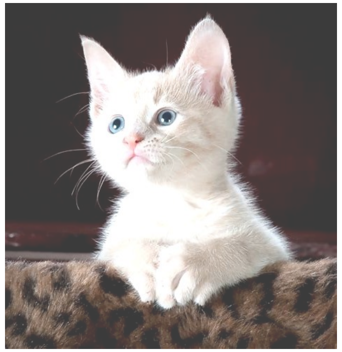
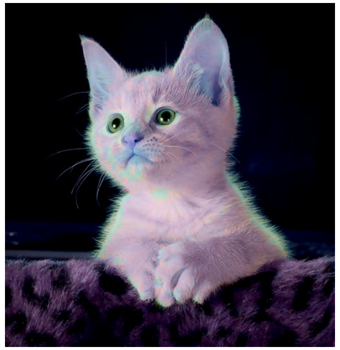


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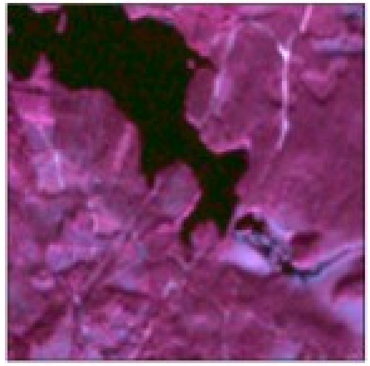

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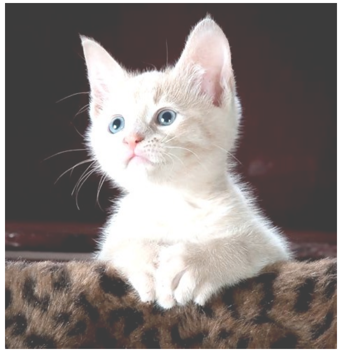
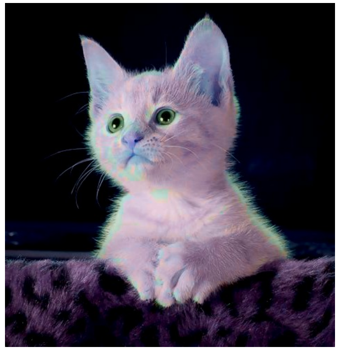


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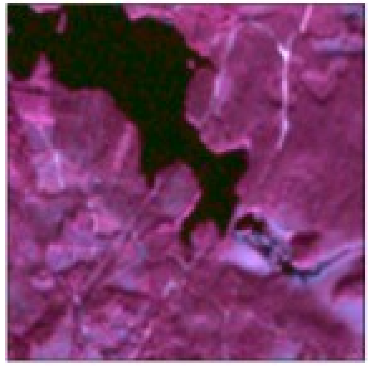


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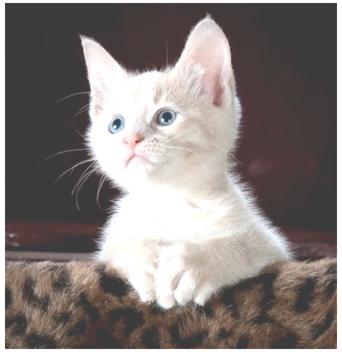

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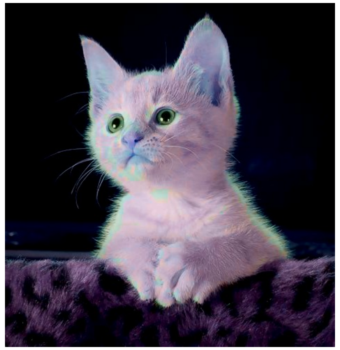

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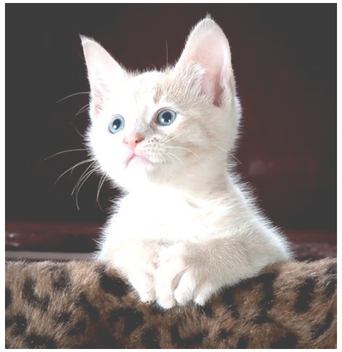

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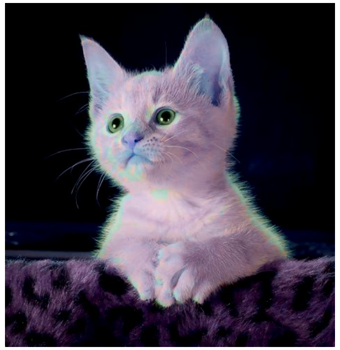

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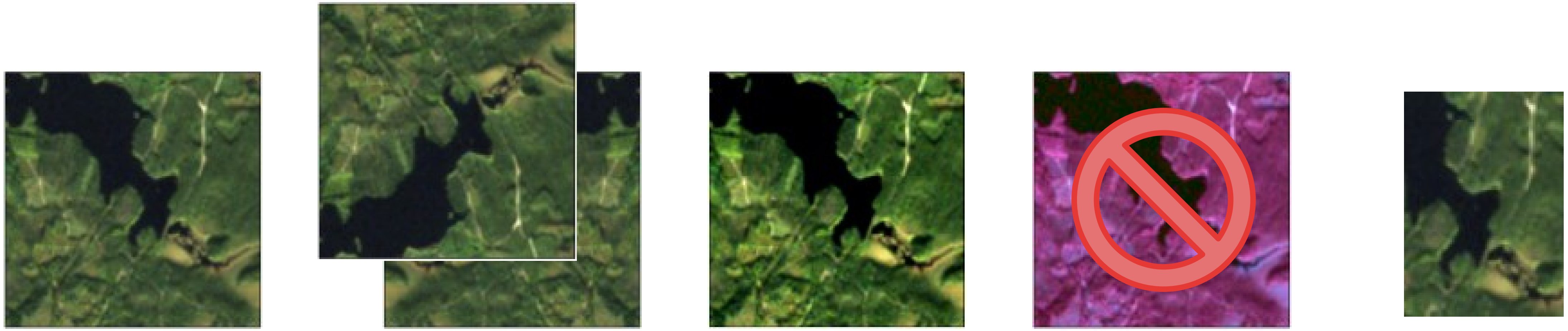

+ Rotations!

Data Augmentations for Remote Sensing

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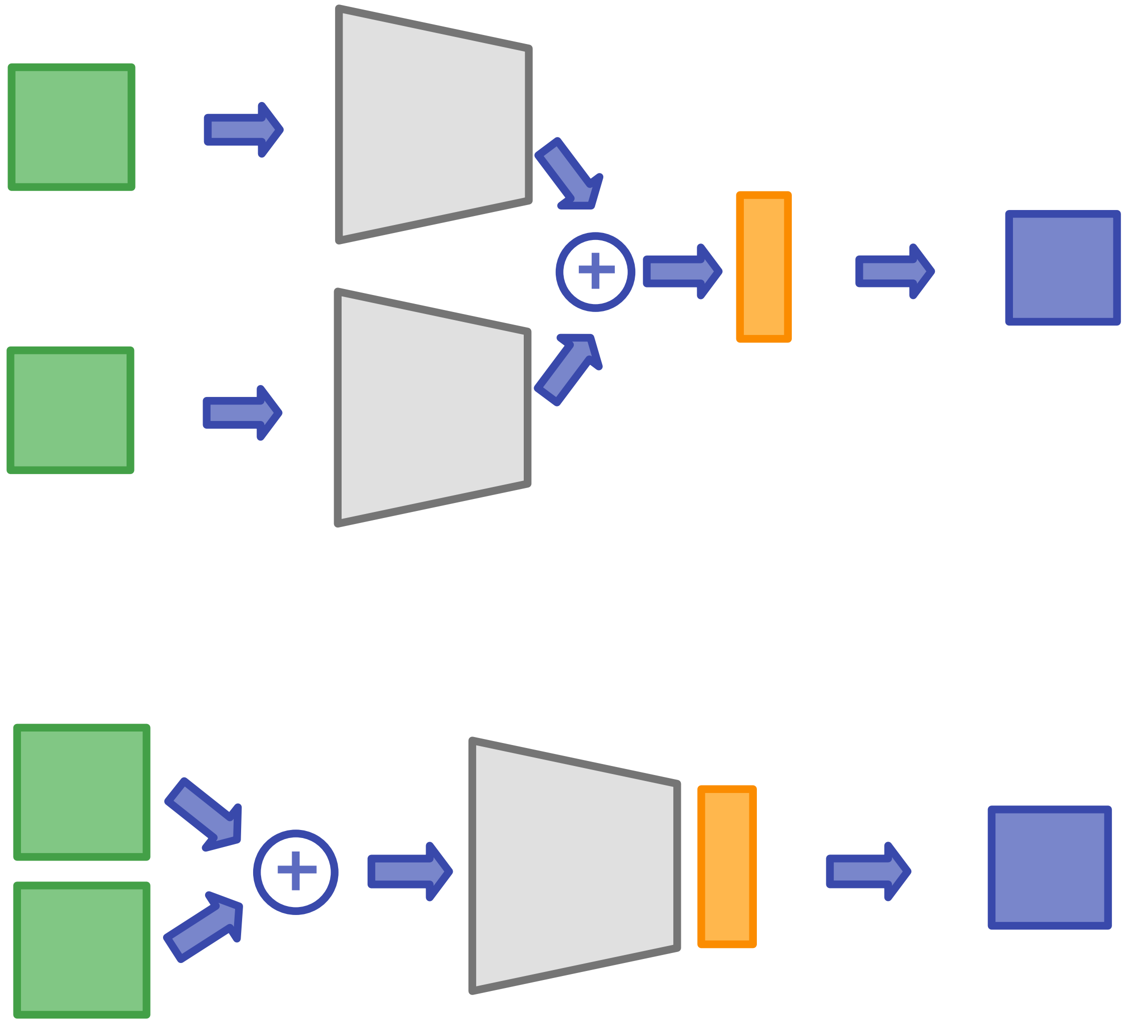
Data augmentations are generally easy to implement, which is why we will not look at them in more detail...

Data Fusion



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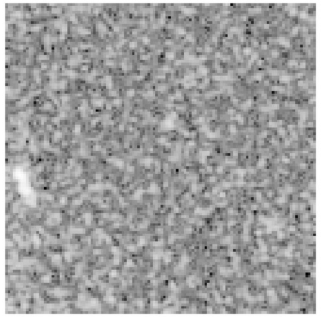

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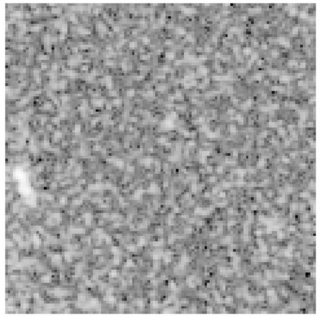

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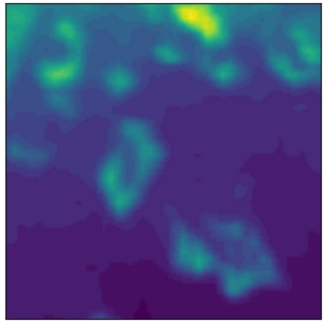

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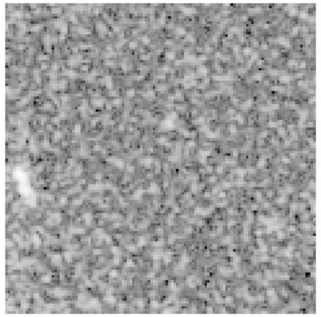

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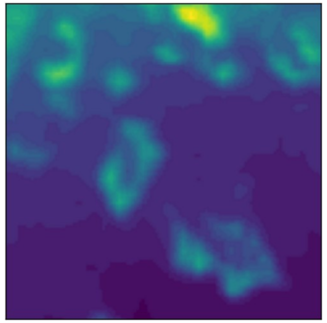

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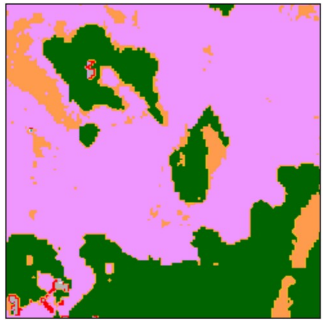

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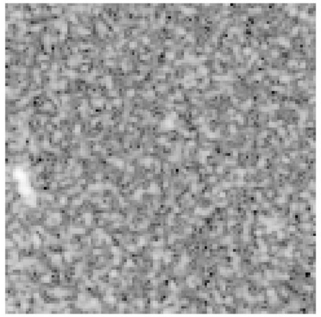

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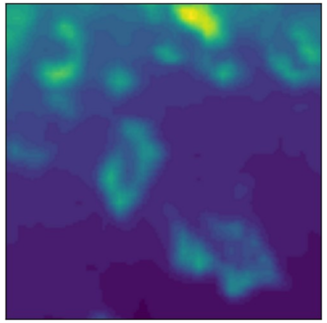

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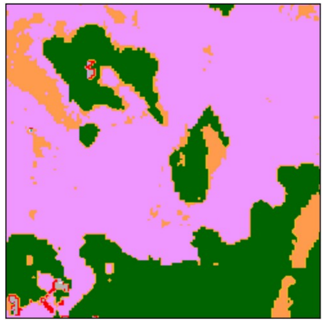

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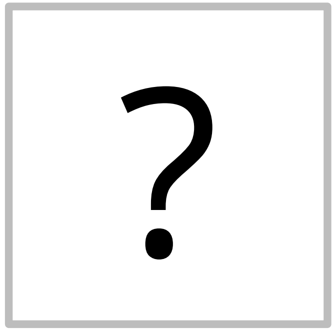

Meta Data
(e.g., weather data, observation circumstances)

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Paolo Gamba will present Data Fusion for change detection in urban areas tomorrow!

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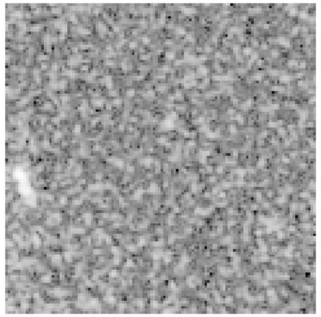

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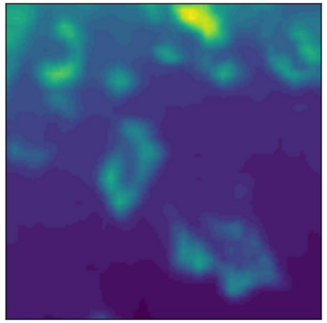

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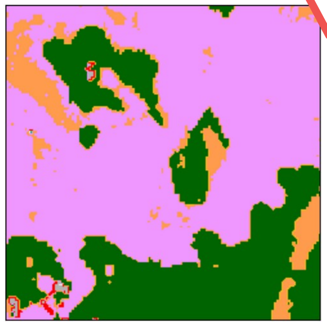

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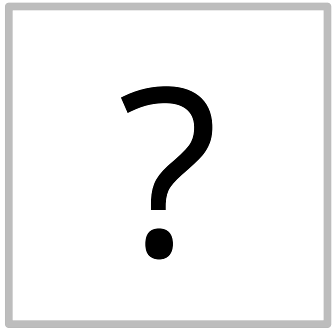

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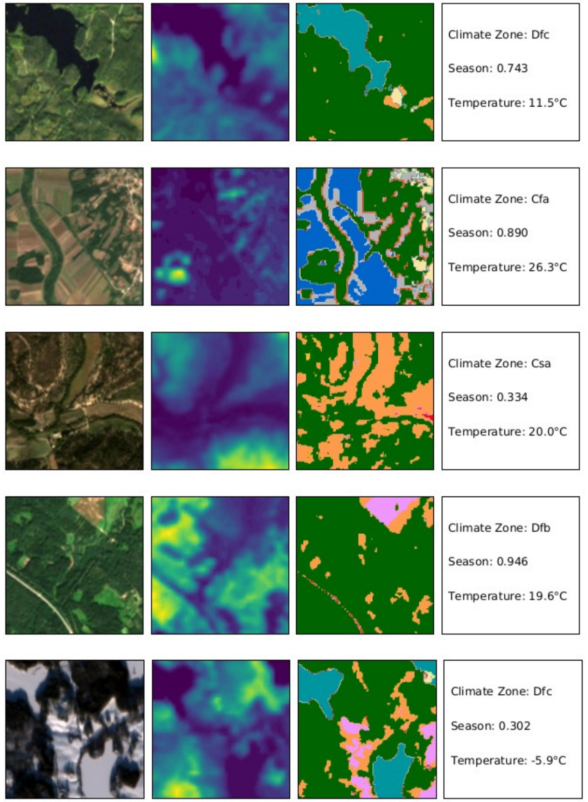

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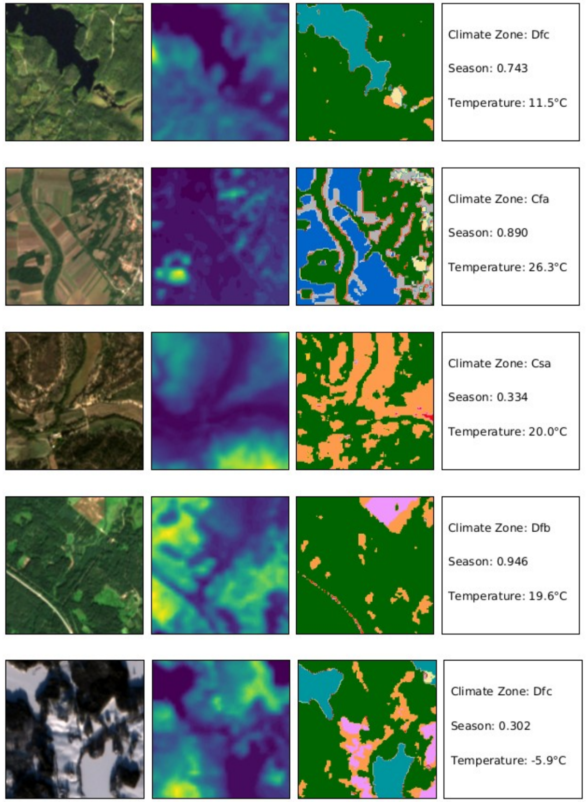

BigEarthNet contains 590,326 patches of co-located Sentinel-1/2 data.

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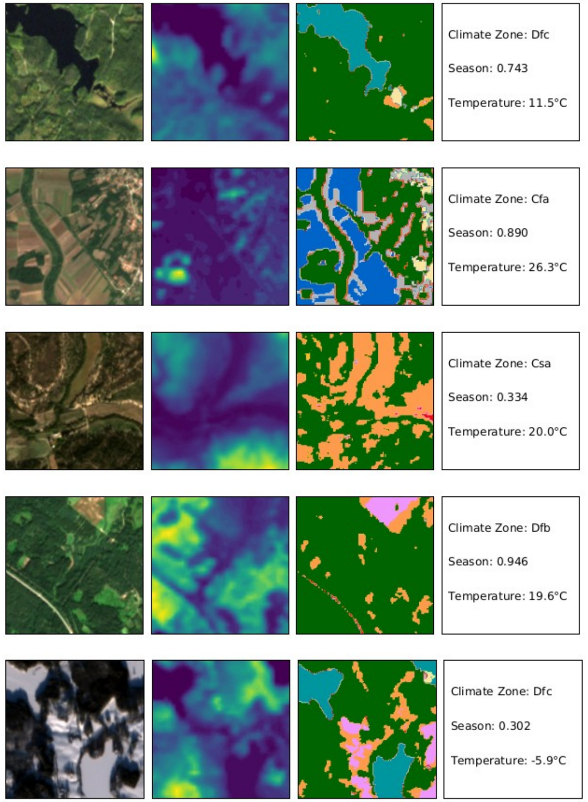

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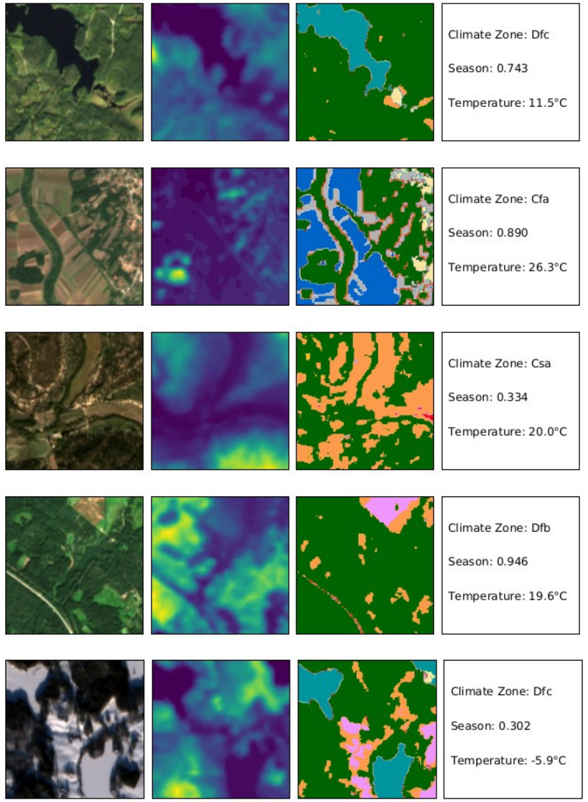

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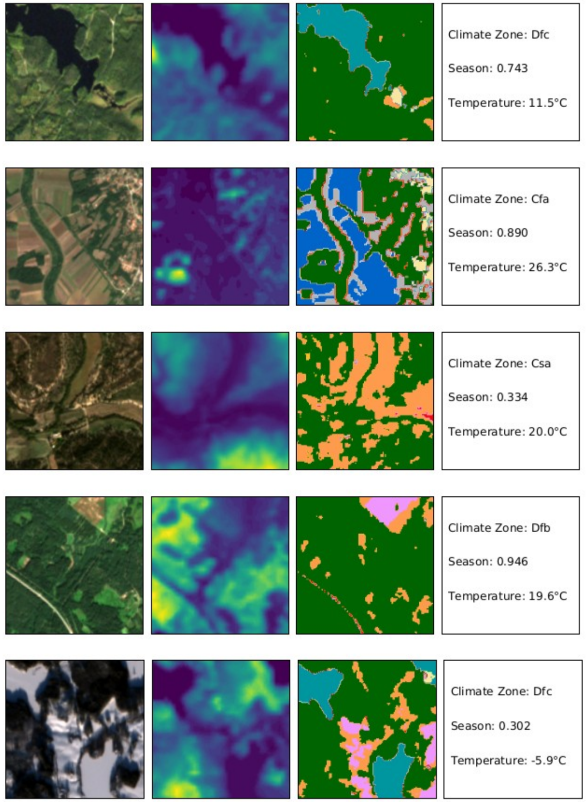

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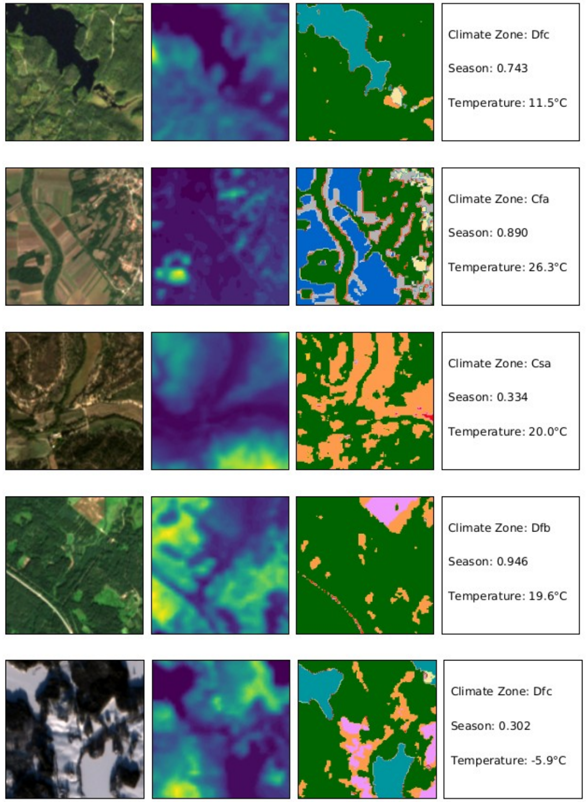

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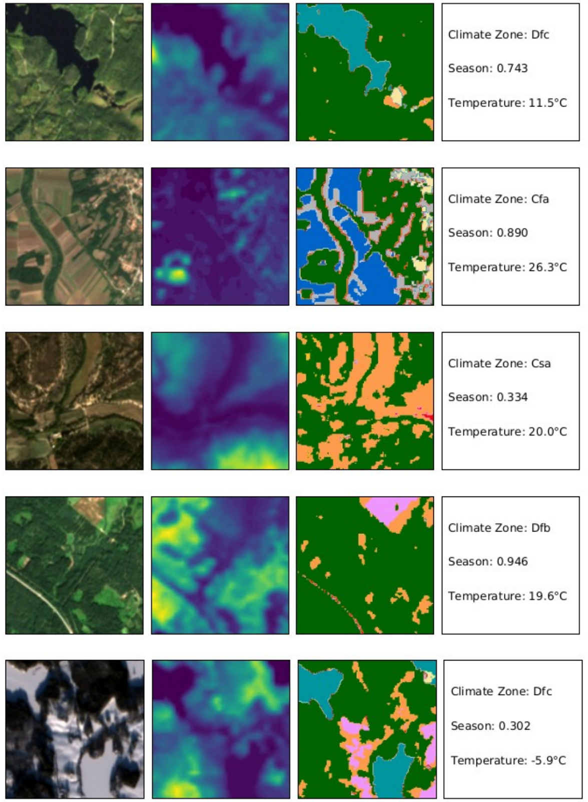

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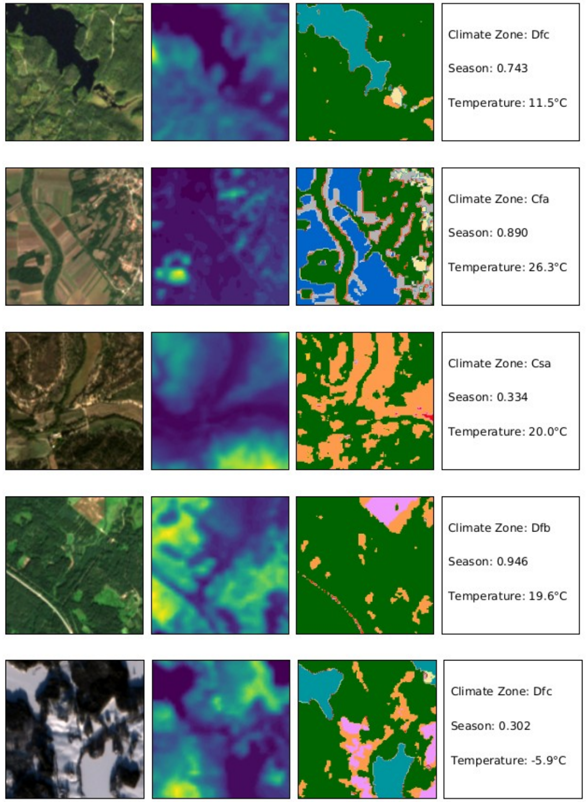

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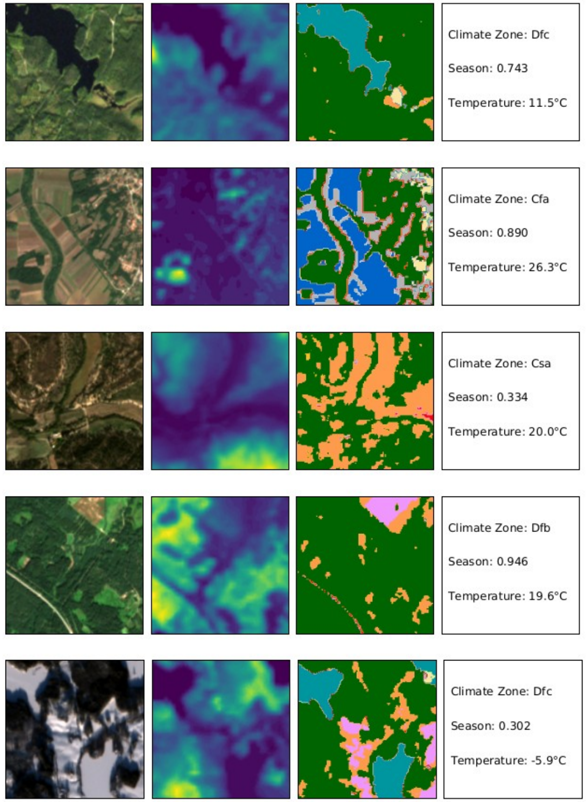

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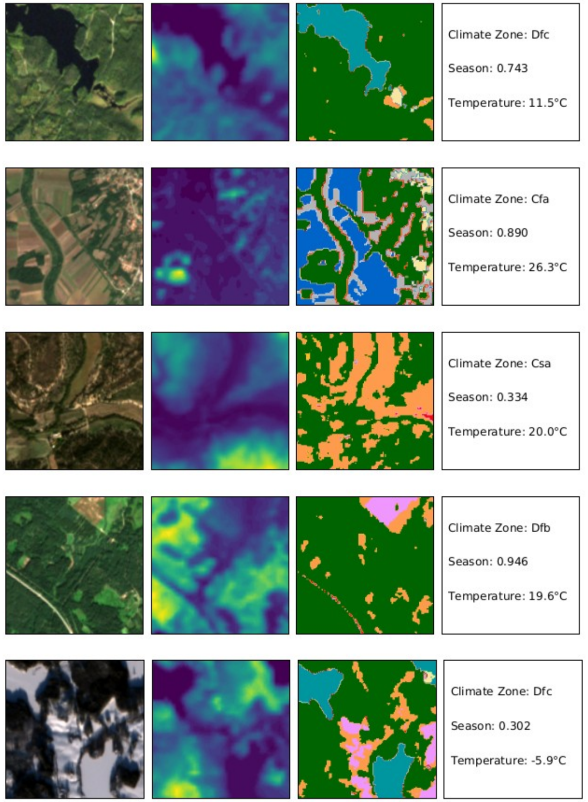

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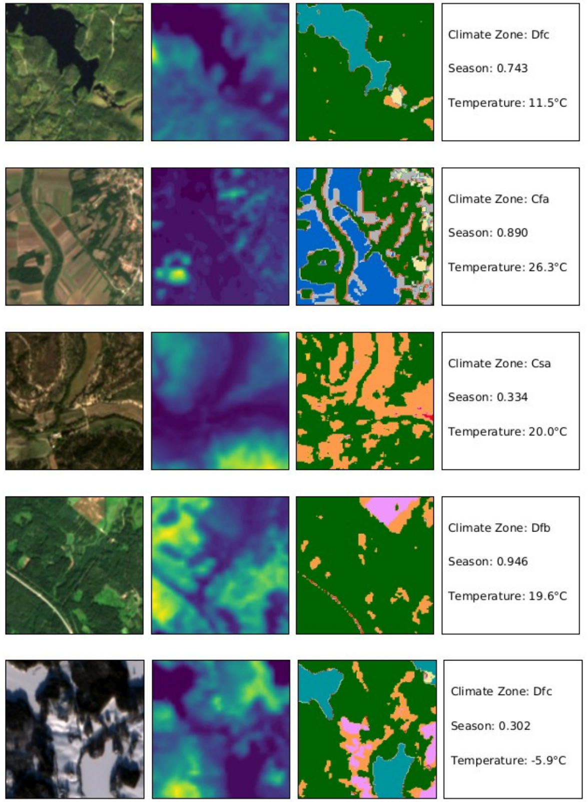

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We will use a subset of ben-ge, ben-ge-800, in this tutorial.

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Multispectral

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Level-2A

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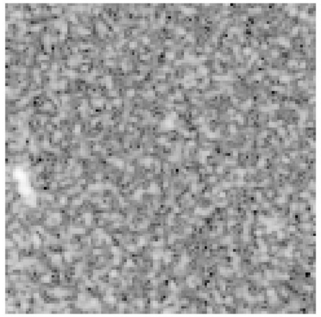


Sentinel-1
SAR

2 bands

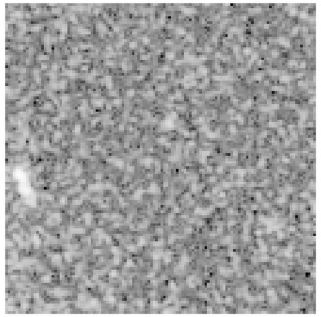
ben-ge: a truly multimodel dataset for EO

What data modalities are available in ben-ge?

BigEarthNet-MM

Sentinel-2
Multispectral

12 bands
Level-2A



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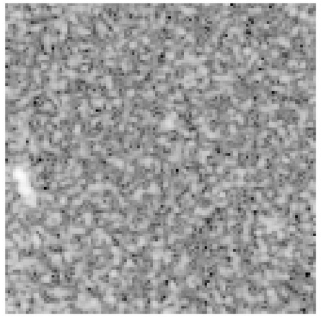

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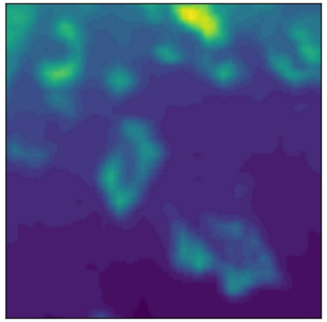

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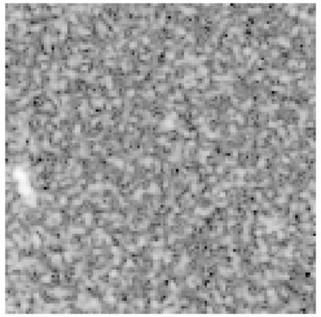

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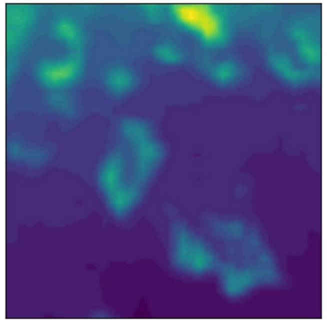

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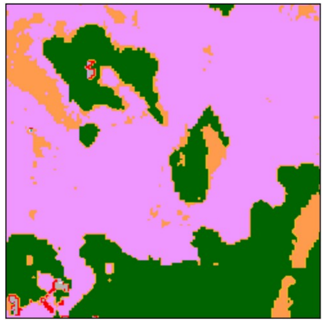

ESA WorldCover
LU/LC

8/11 classes

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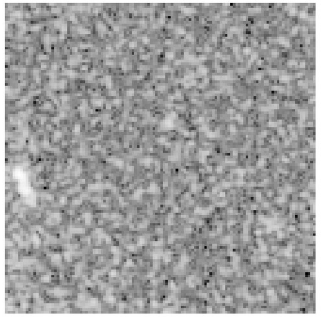

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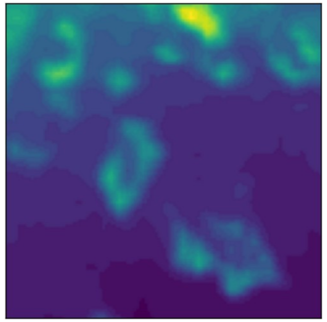

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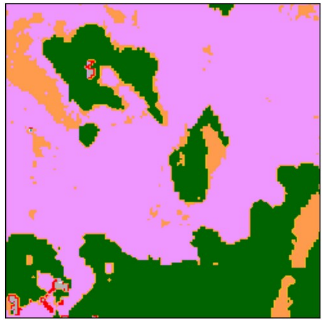

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Meta Data

ERA-5 weather
Climate zones
Seasonality

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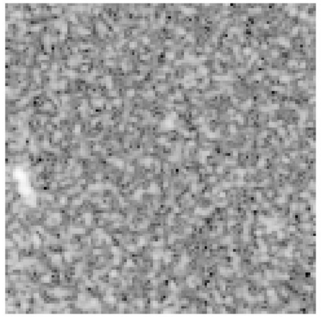

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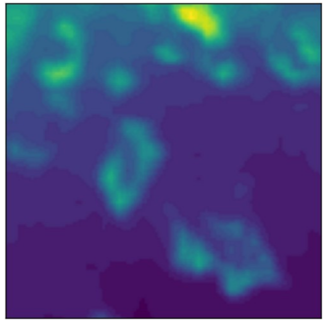

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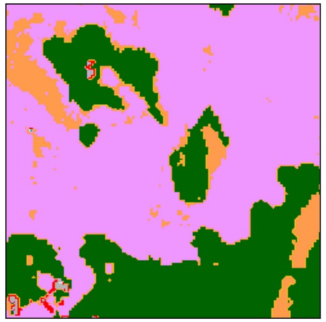

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Seasonality

10m resolution

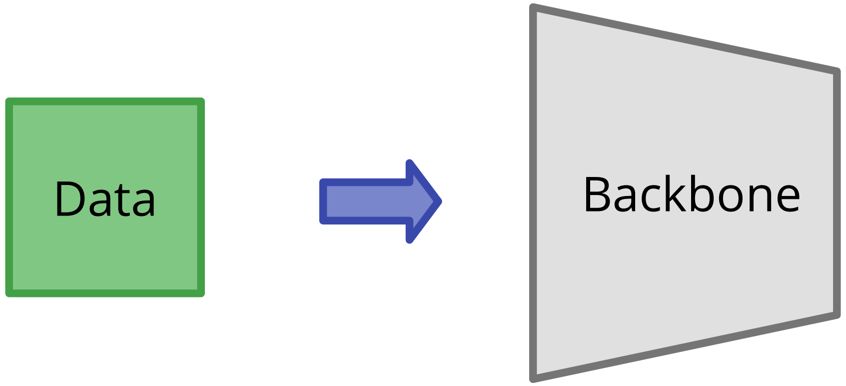
How can we leverage Data Fusion in Deep Learning?

Default supervised learning setup

Data

"Default supervised learning setup"

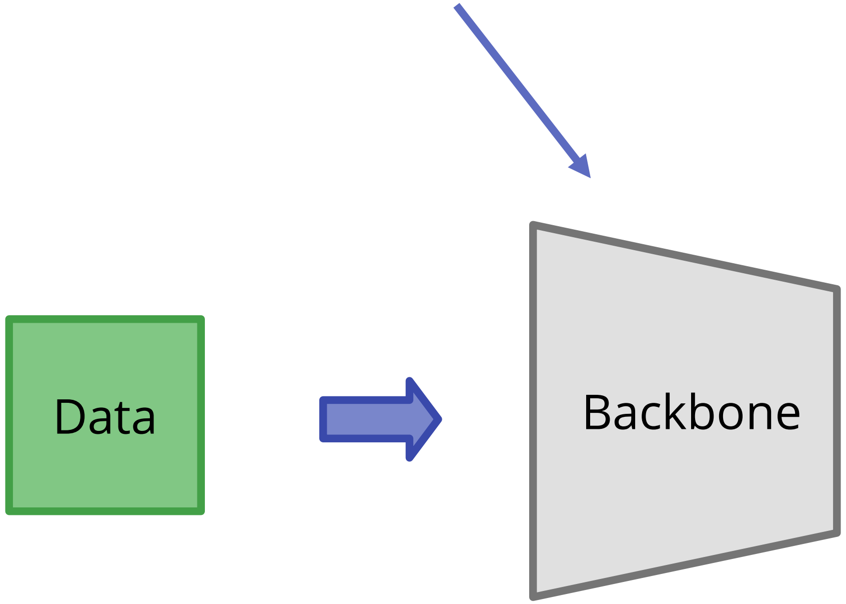
Default supervised learning setup



“Default supervised learning setup”

Default supervised learning setup

Feature extractor
(in this tutorial: U-Net)



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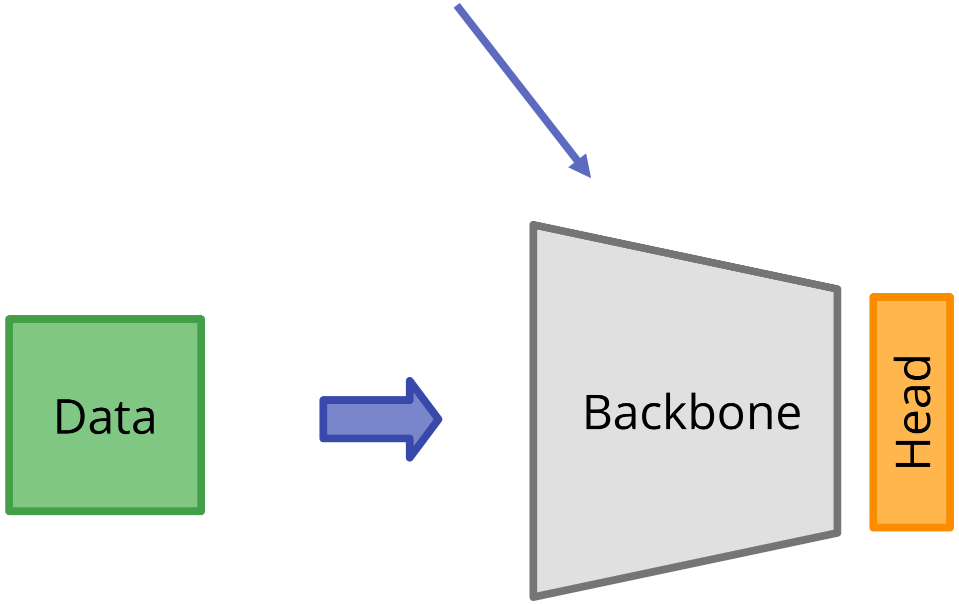

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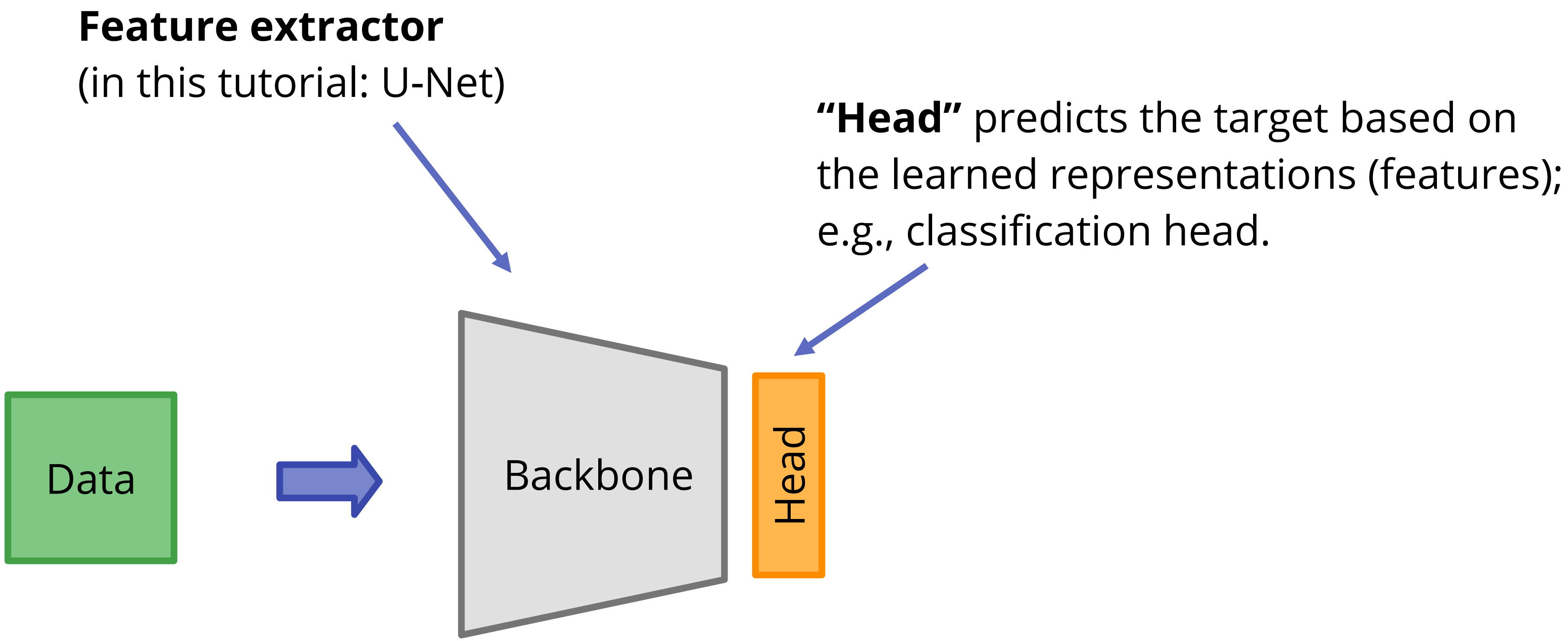

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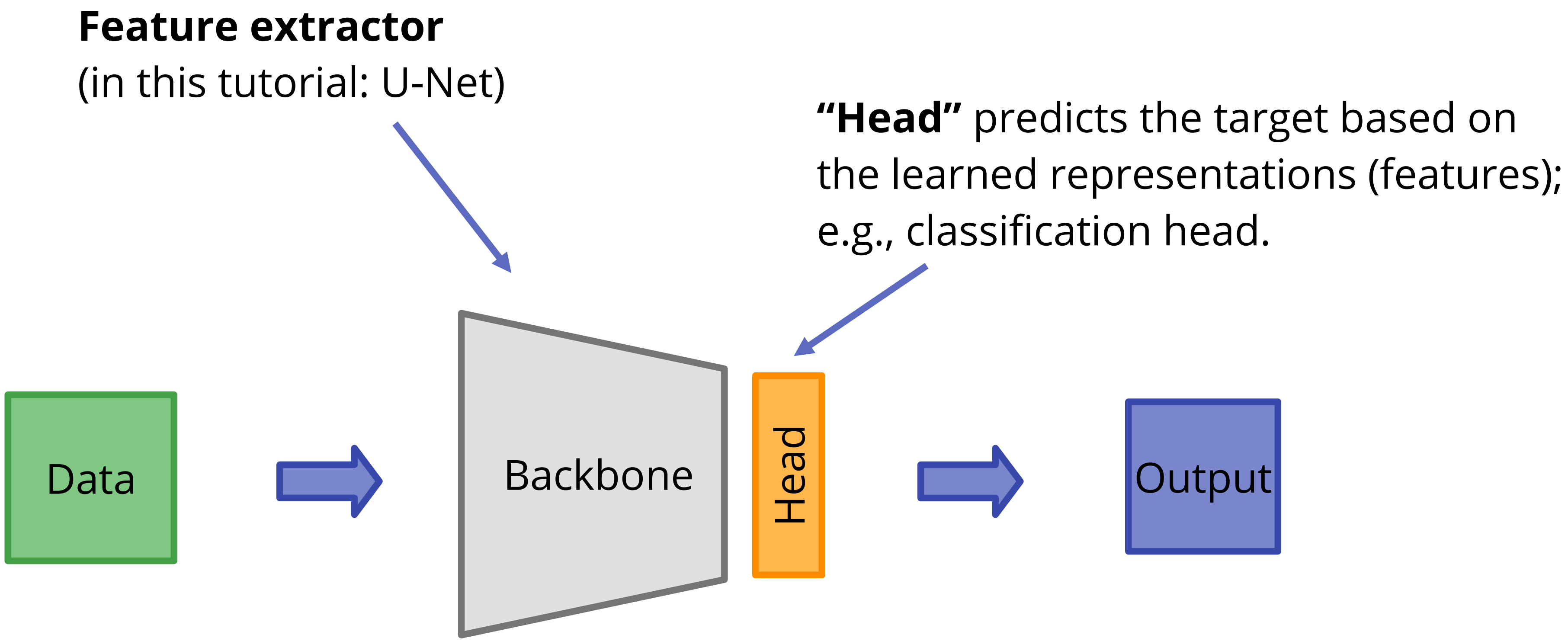

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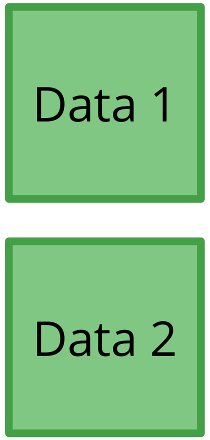

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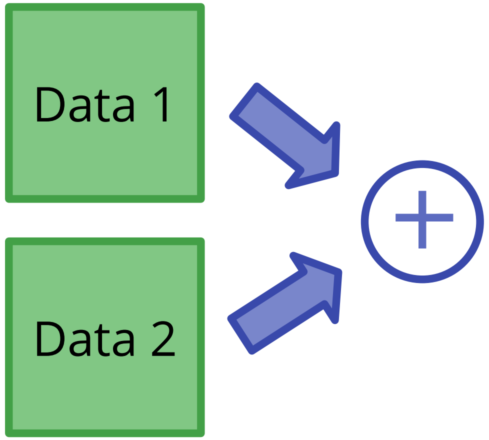

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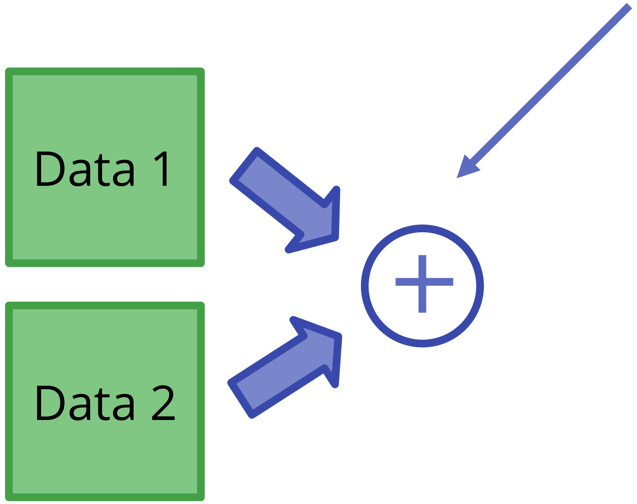
Concatenation: stack data (all of the same shape) along the channel axis



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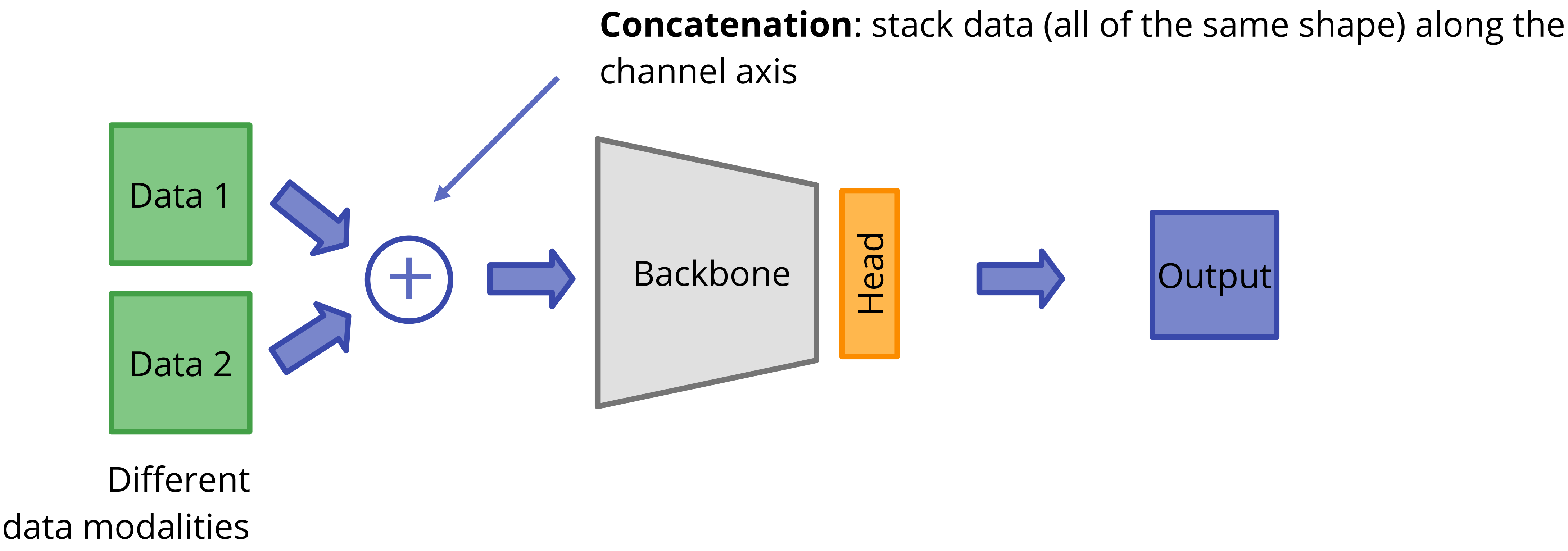

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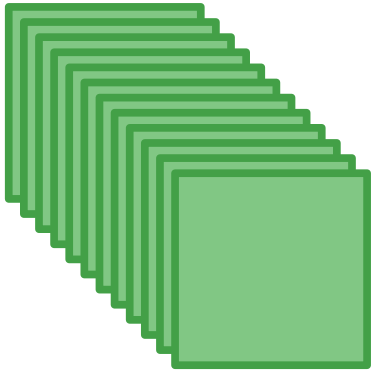

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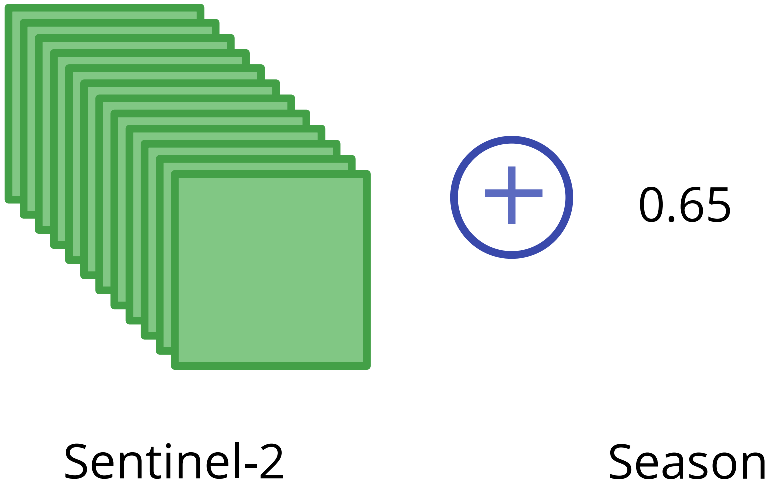

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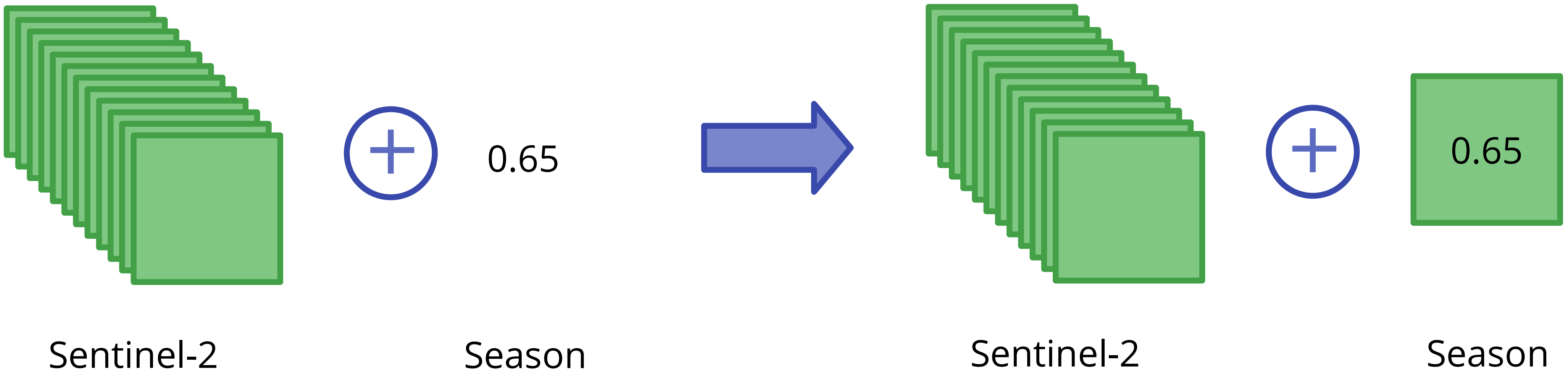

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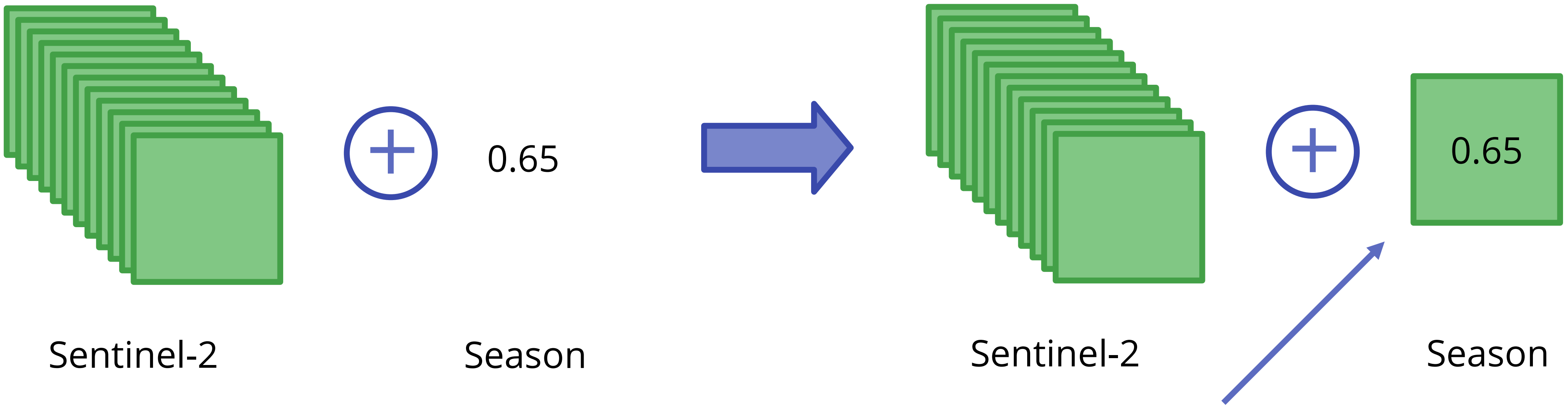

Blow-up patch: same height and width as Sentinel-2; each "pixel" equals the global value (0.65)

Late Fusion

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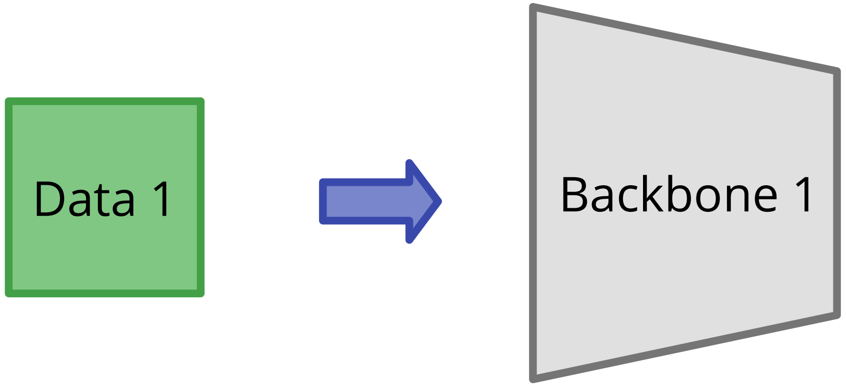

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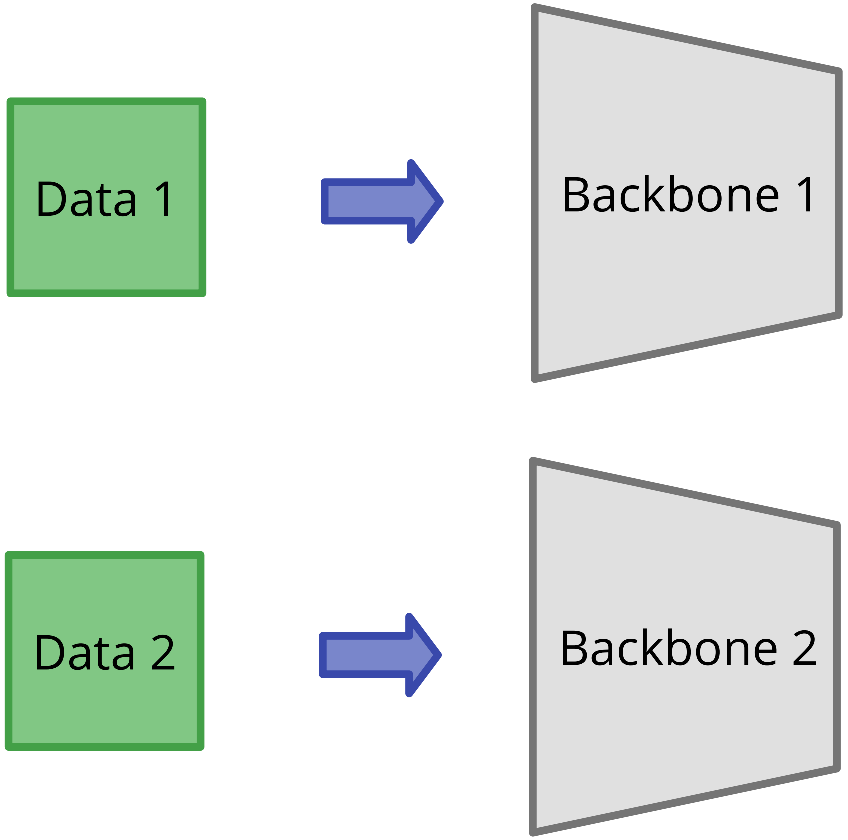

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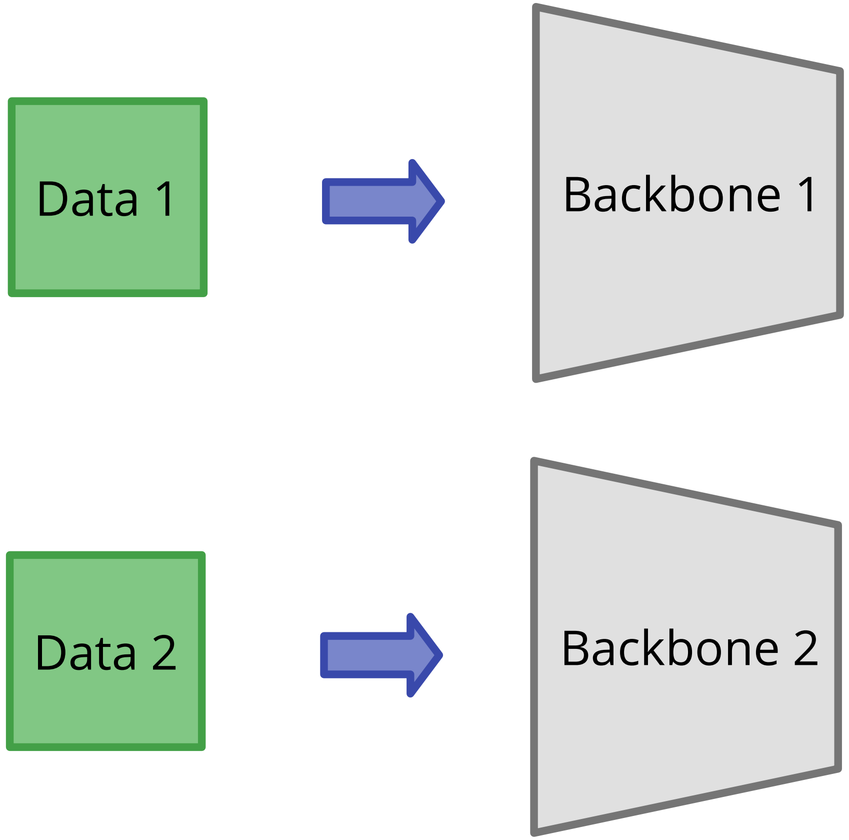

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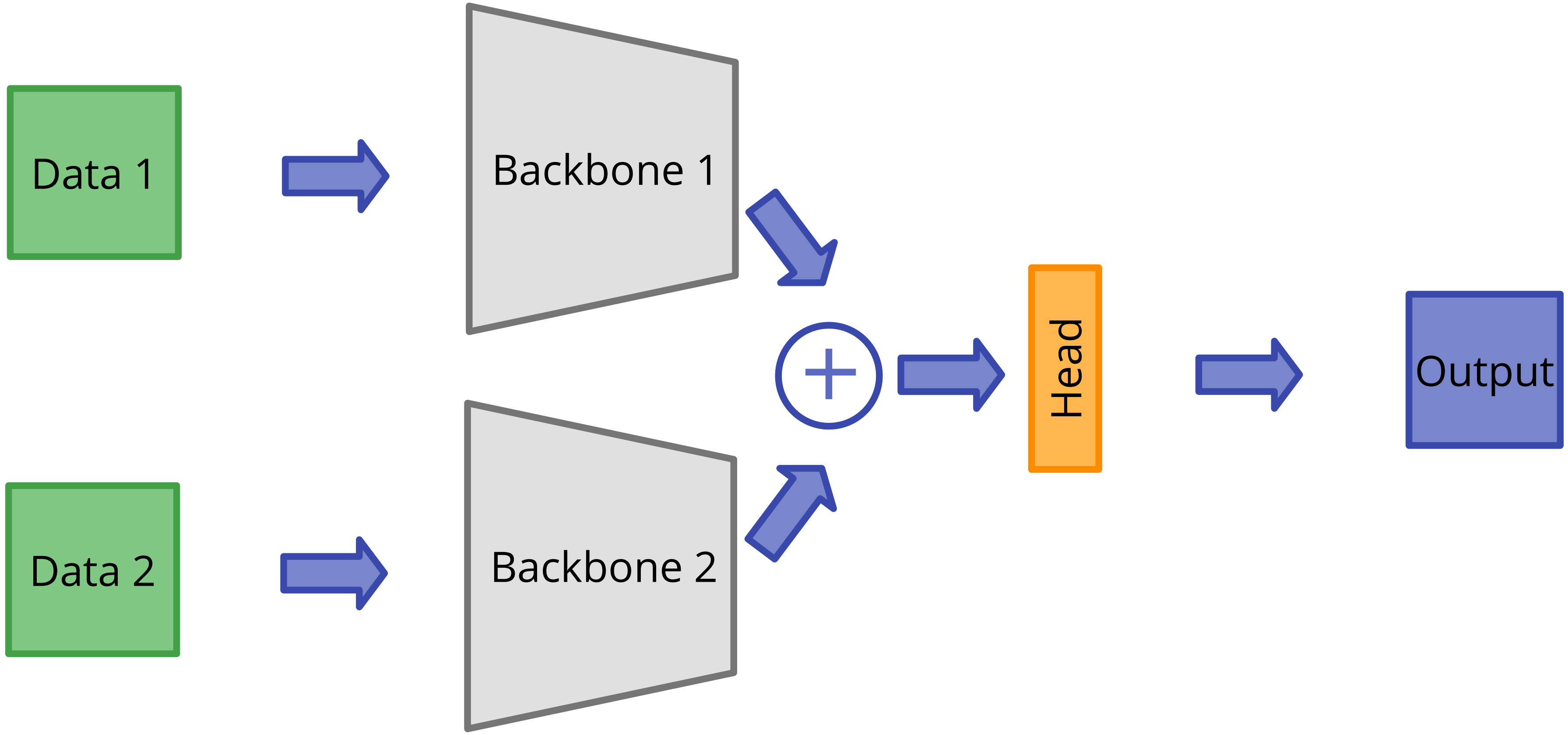

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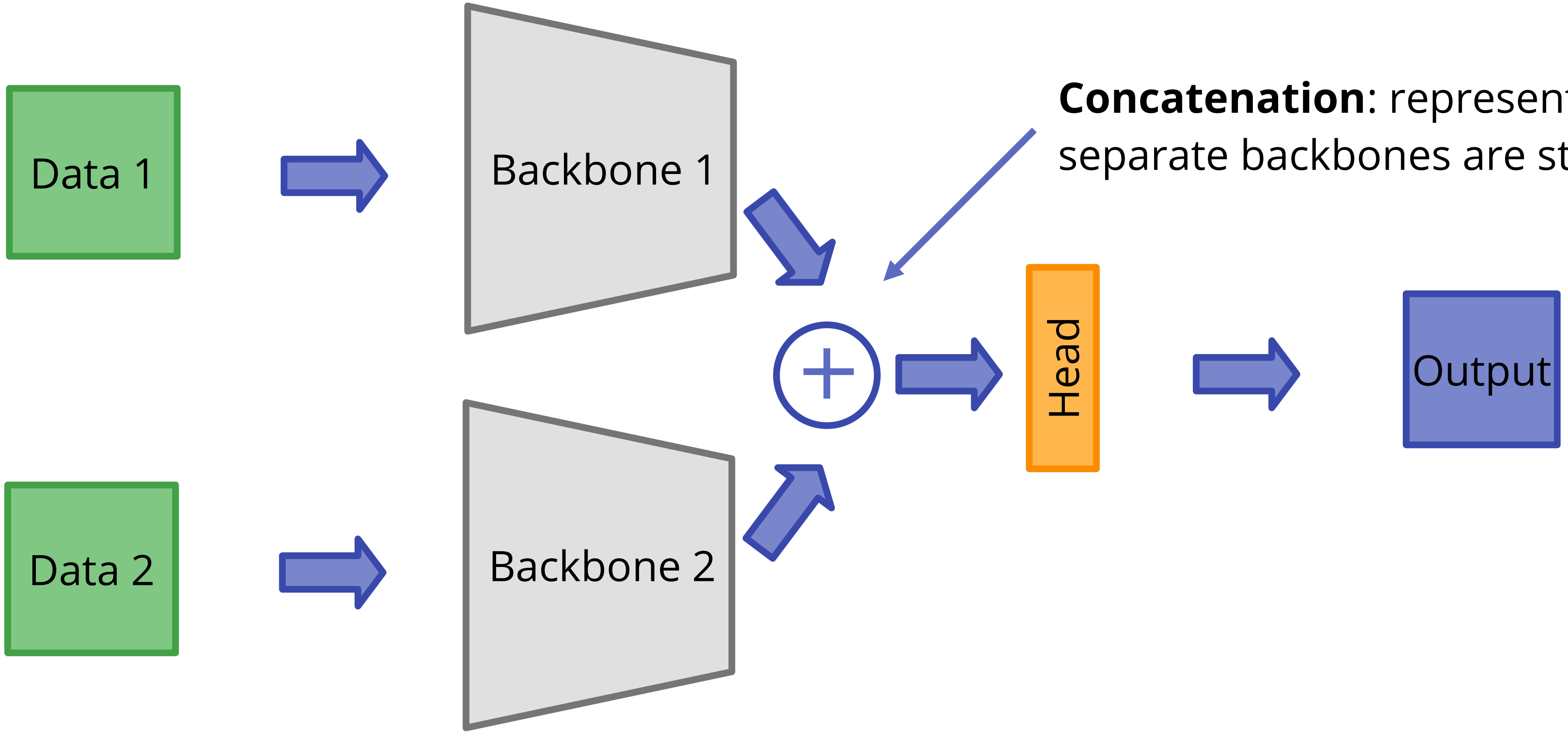

Concatenation: representations emerging from separate backbones are stacked along either axis

Backbones might be completely separate, or have shared weights.

Let’s implement some Data Fusion techniques into our model!

Data Fusion: An example

Which data modalities make sense to combine? (Mommert et al. 2023)

N	Sen-2	Sen-1	Climate	DEM	Weather	Season	Classification [%] F1-score	Classification [%] Accuracy	Segmentation [%] IoU	Segmentation [%] Accuracy
1	✓						**77.12**±0.64	96.21±0.08	**39.17**±0.09	87.57±0.05
		✓					73.09±0.24	95.60±0.05	31.70±0.17	82.65±0.05
			✓				70.50±0.34	94.69±0.03	14.70±0.32	60.65±1.35
				✓			55.96±1.00	93.53±0.15	26.25±0.48	76.92±0.63
					✓		46.15±0.68	91.60±0.02	6.30±0.05	45.20±0.08
						✓	39.15±0.74	91.75±0.05	6.01±0.34	43.89±0.51
2	✓	✓					**82.81**±0.29	97.03±0.04	**39.67**±0.16	87.98±0.07
	✓					✓	78.61±0.67	96.42±0.08	38.92±0.21	87.37±0.10
3	✓	✓	✓				**85.12**±0.34	97.39±0.05	39.63±0.23	87.94±0.12
	✓	✓		✓			83.30±0.43	97.10±0.08	**39.71**±0.21	88.05±0.11
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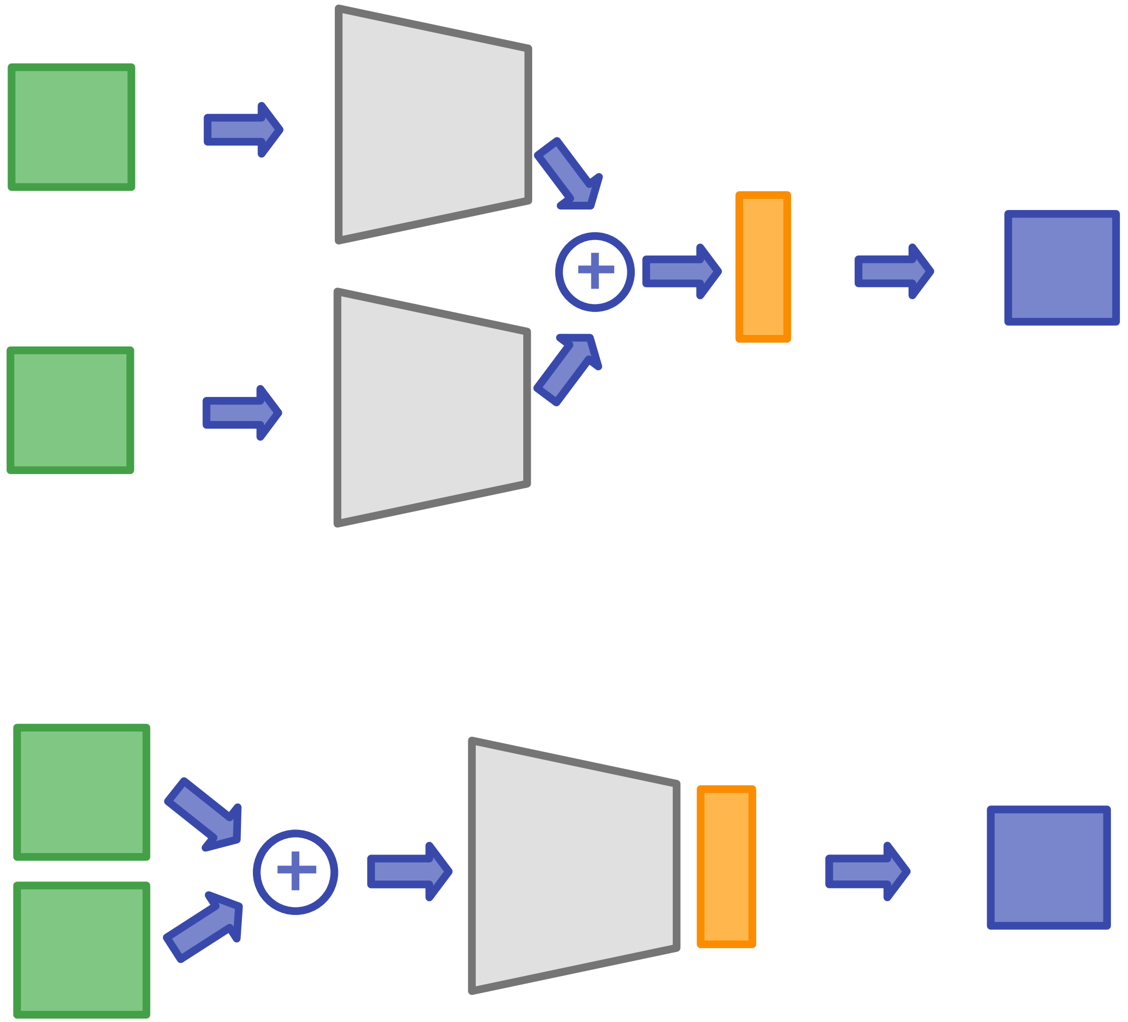
Which method is better: in most cases, late fusion seems to be more beneficial (might be a fallacy).

Multitask Learning



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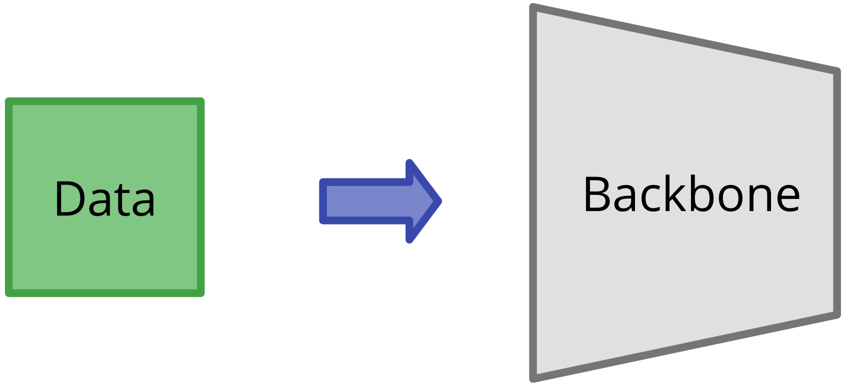

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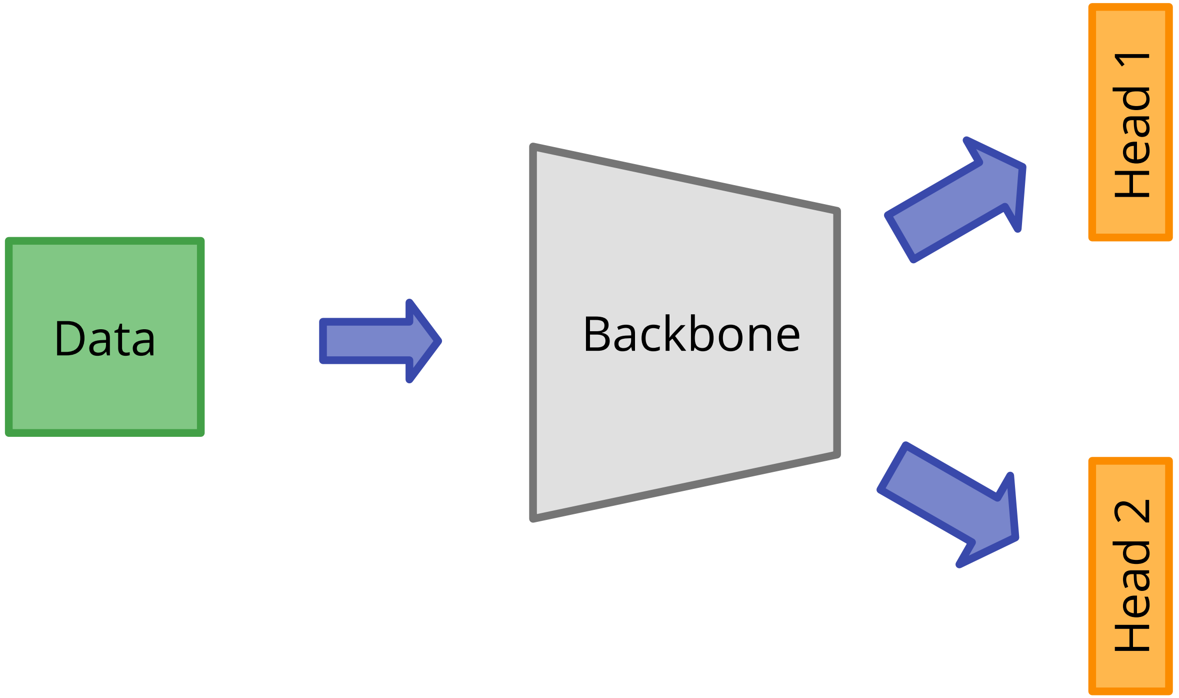

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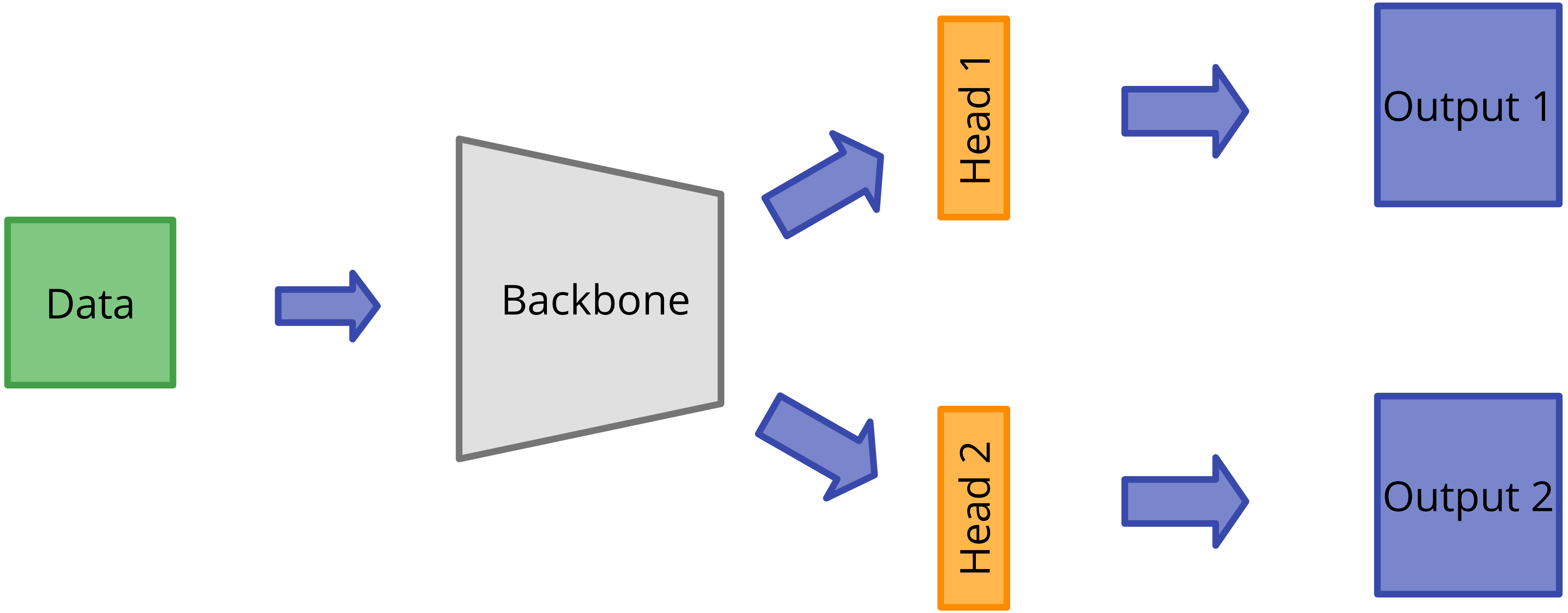
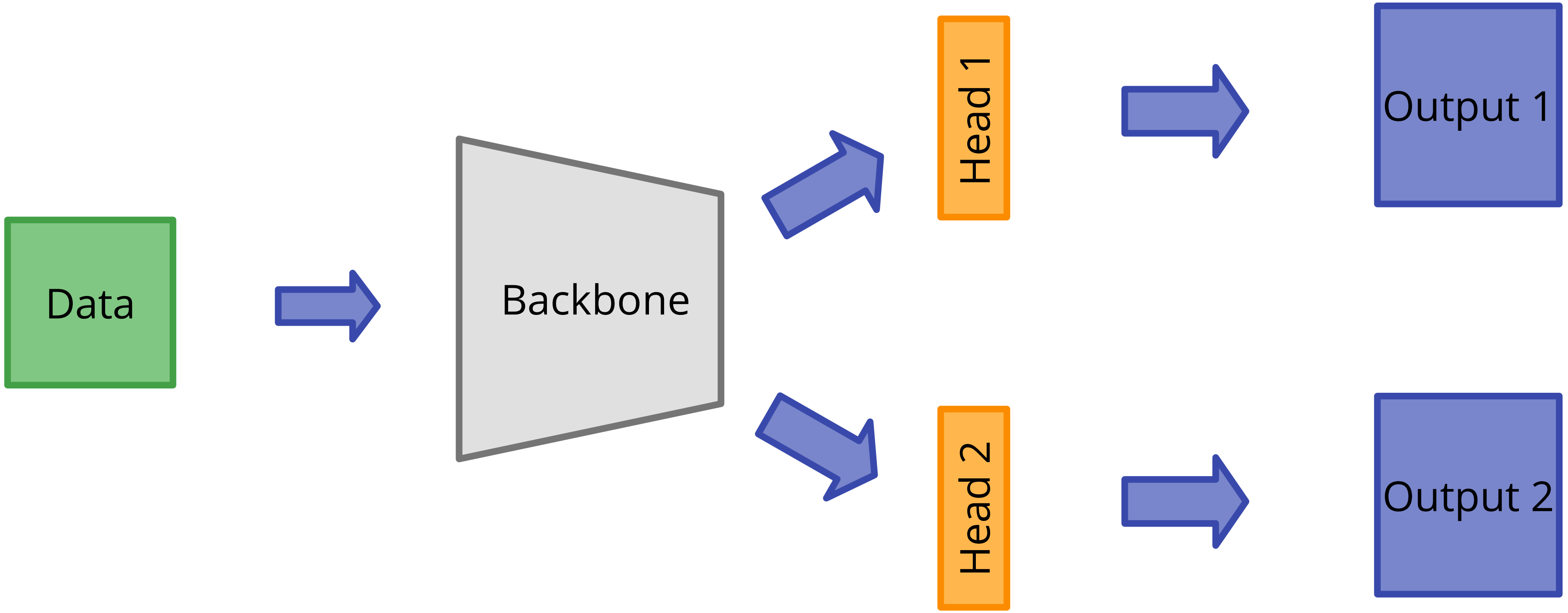


How are multitask architectures trained?



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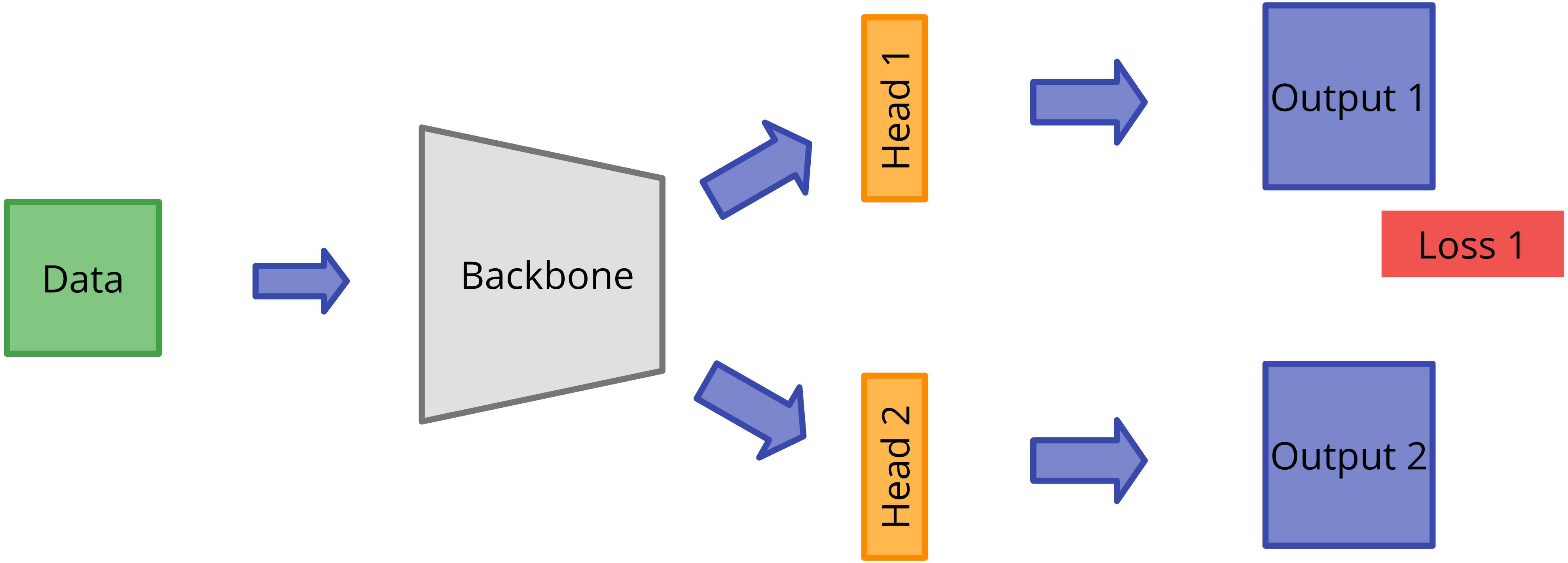

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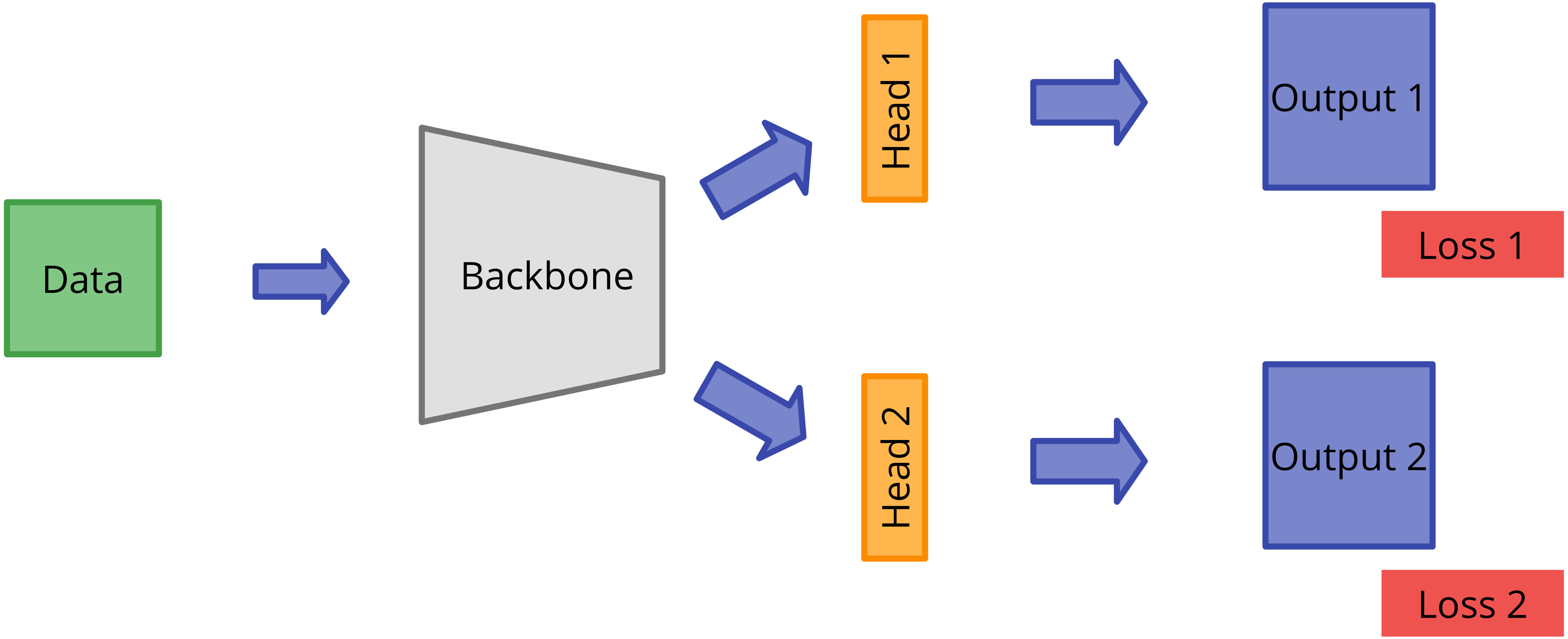

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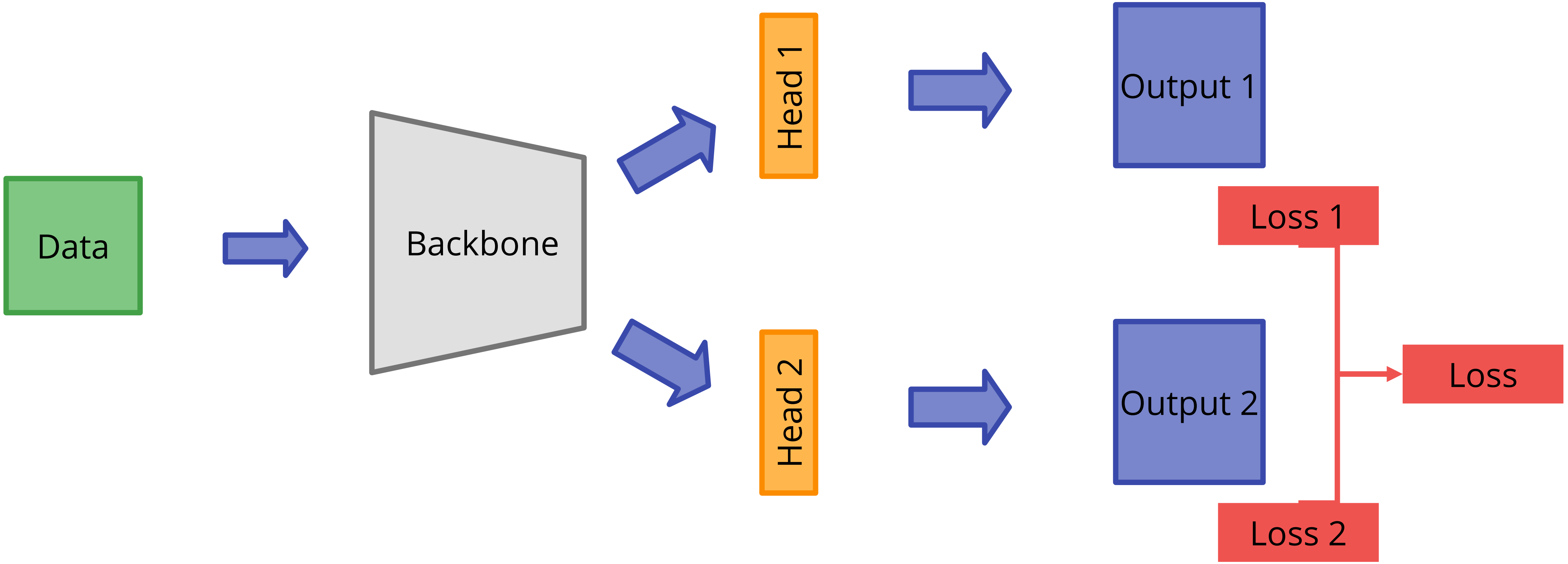

The Loss of the combined architecture is a weighted sum of the Losses of the individual downstream tasks.

Let’s implement some Multitask Learning techniques based on our model!

Multitask Learning: an Example

Idea: Can we train a neural network to estimate power and CO_2 output of power plants?

Hanna et al. (2023)

Multitask Learning: an Example

Idea: Can we train a neural network to estimate power and CO_2 output of power plants?

~3000 observations of
~150 power plants

Sentinel-2
12 Bands

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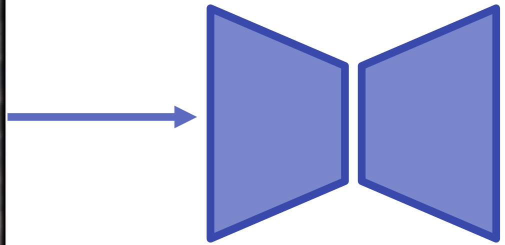

Backbone
(U-Net)

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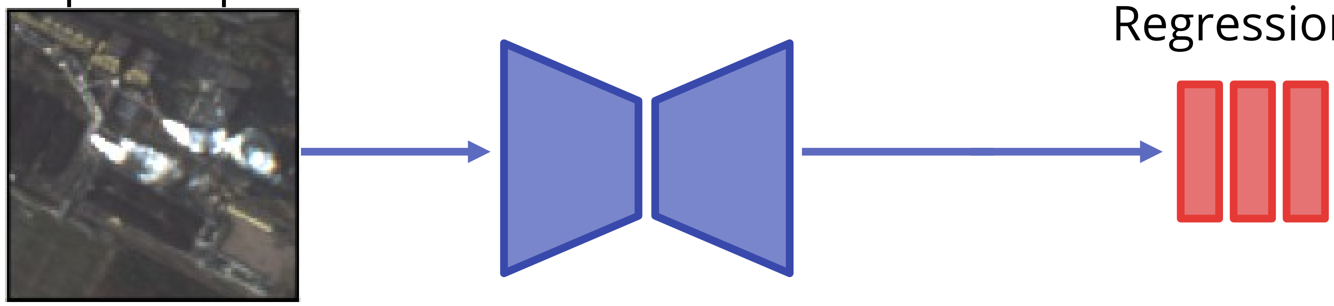

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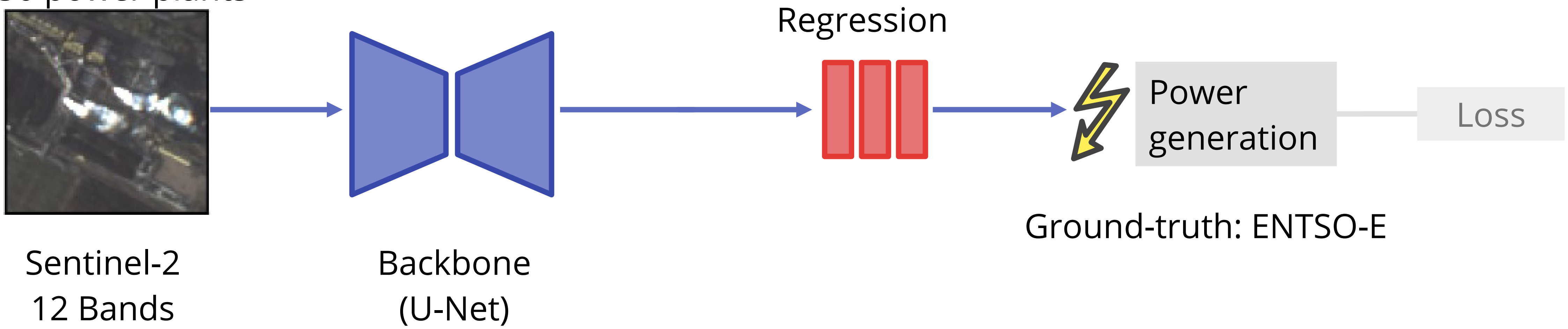

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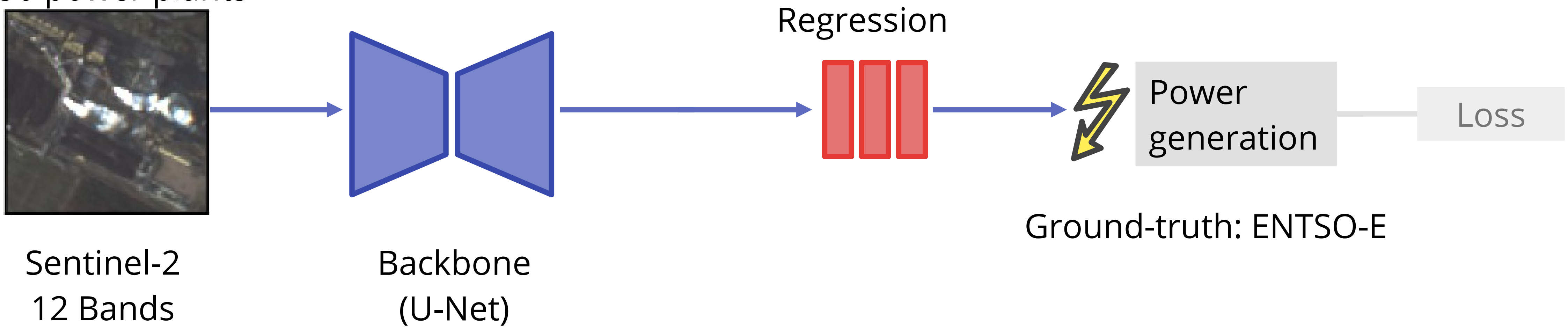
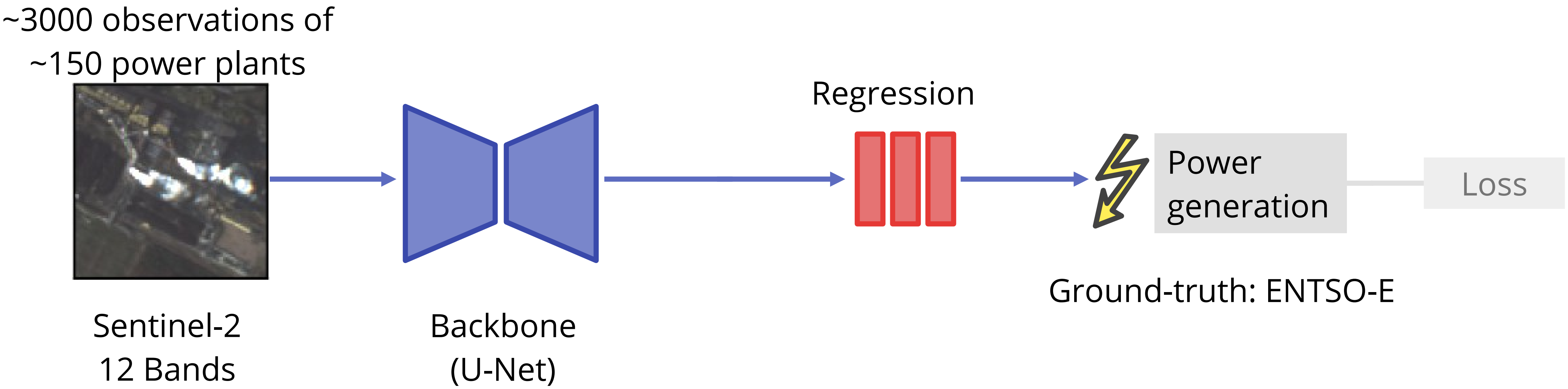


Regression:	MAE [MW]	R^2
Baseline:	202±20	65±5

Hanna et al. (2023)

Multitask Learning: an Example

Idea: Can we train a neural network to estimate power and CO_2 output of power plants?

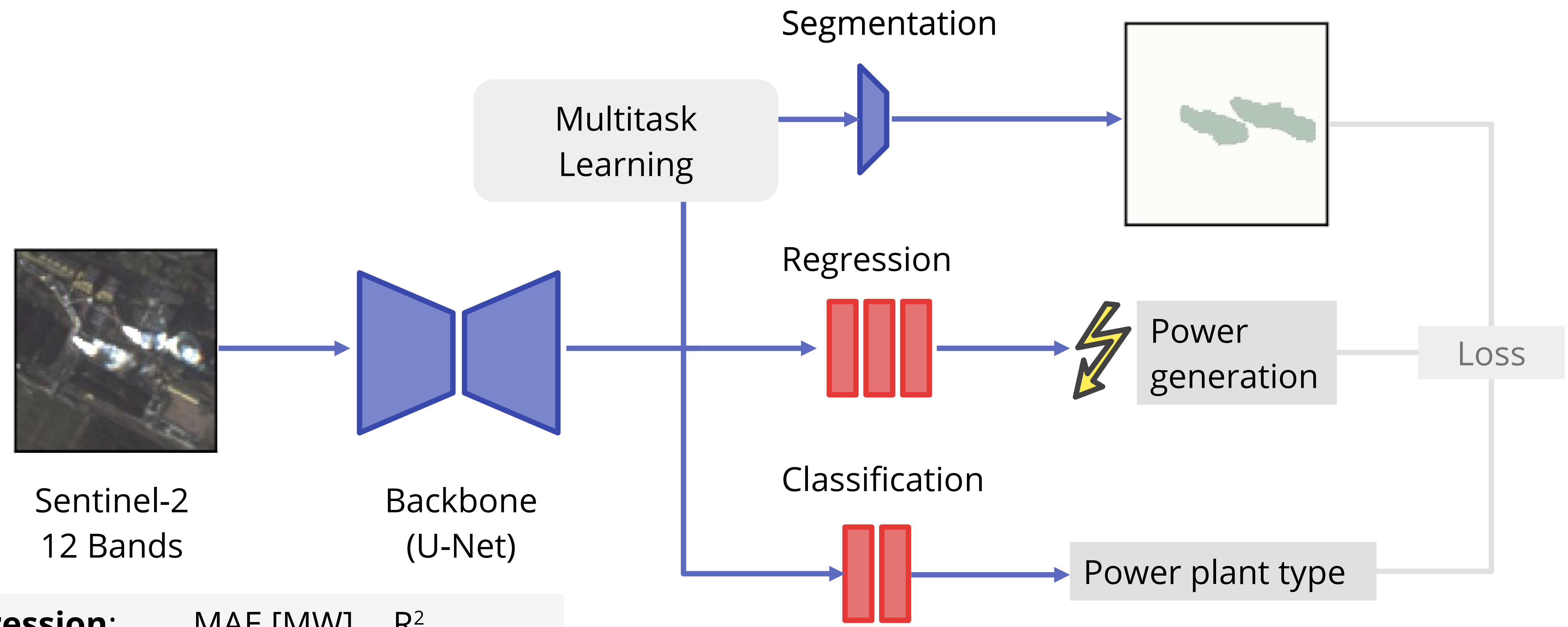


Regression:	MAE [MW]	R^2
Baseline:	202±20	65±5

Estimating power generation is possible. But can we improve it with Multitask learning?

Hanna et al. (2023)

Multitask Learning: an Example

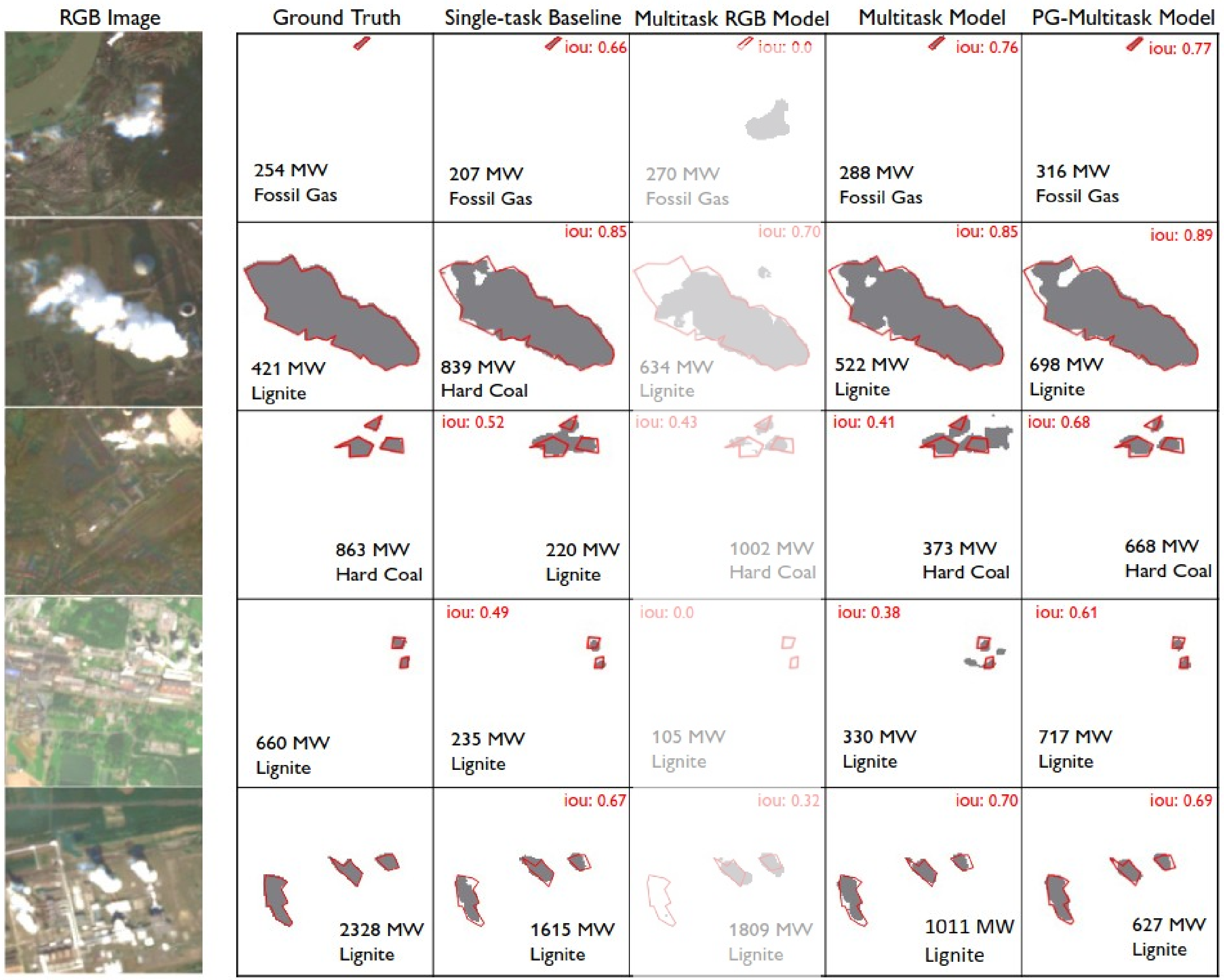


Regression:	MAE [MW]	R^2
Baseline:	202±20	65±5
Multitask:	187±4	66±6

Learning several tasks at the same time improves the performance significantly.

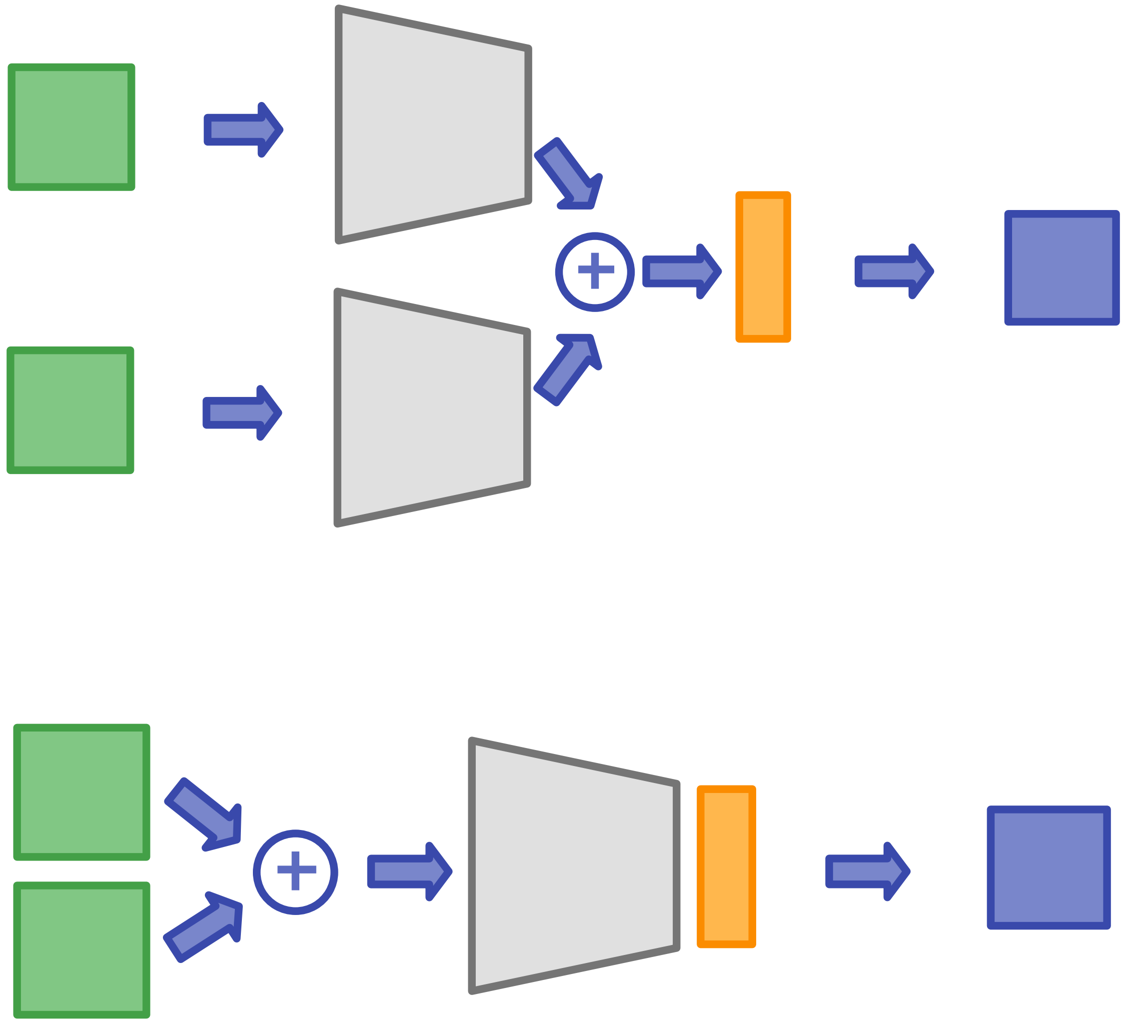
Hanna et al. (2023)

Multitask Learning: an Example

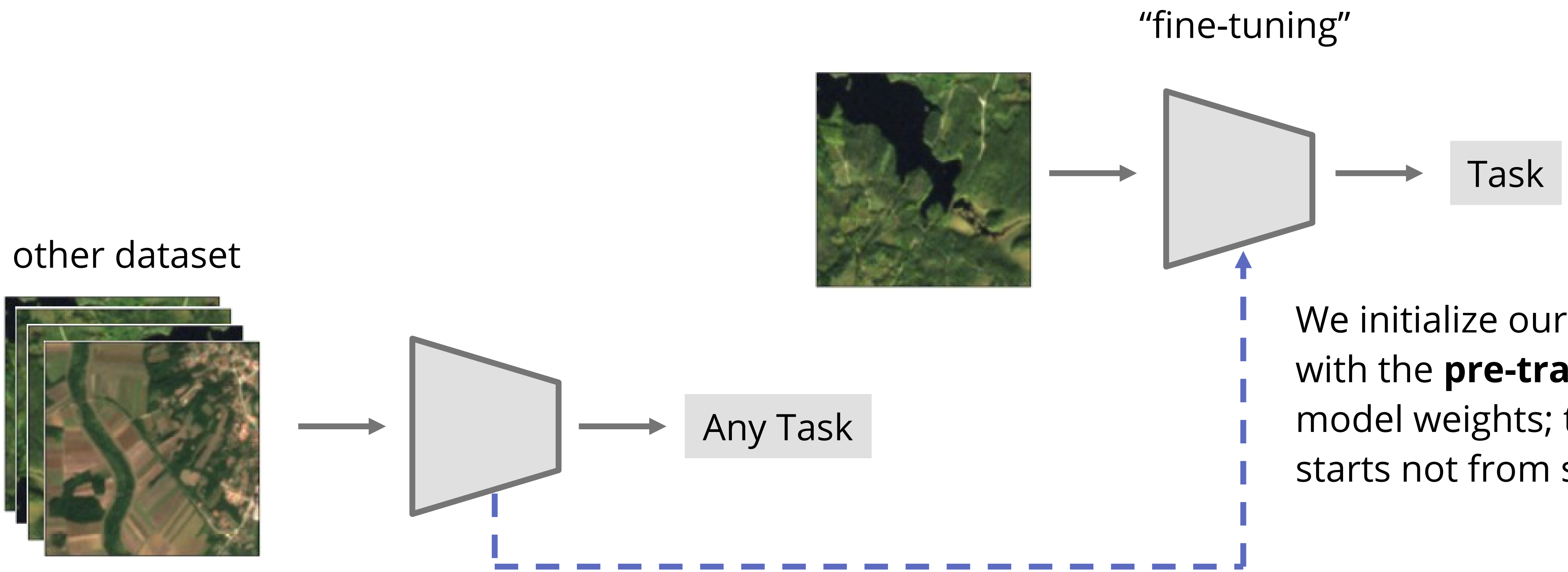


Hanna et al. (2023)

Transfer Learning and Self-supervised Learning



Transfer Learning

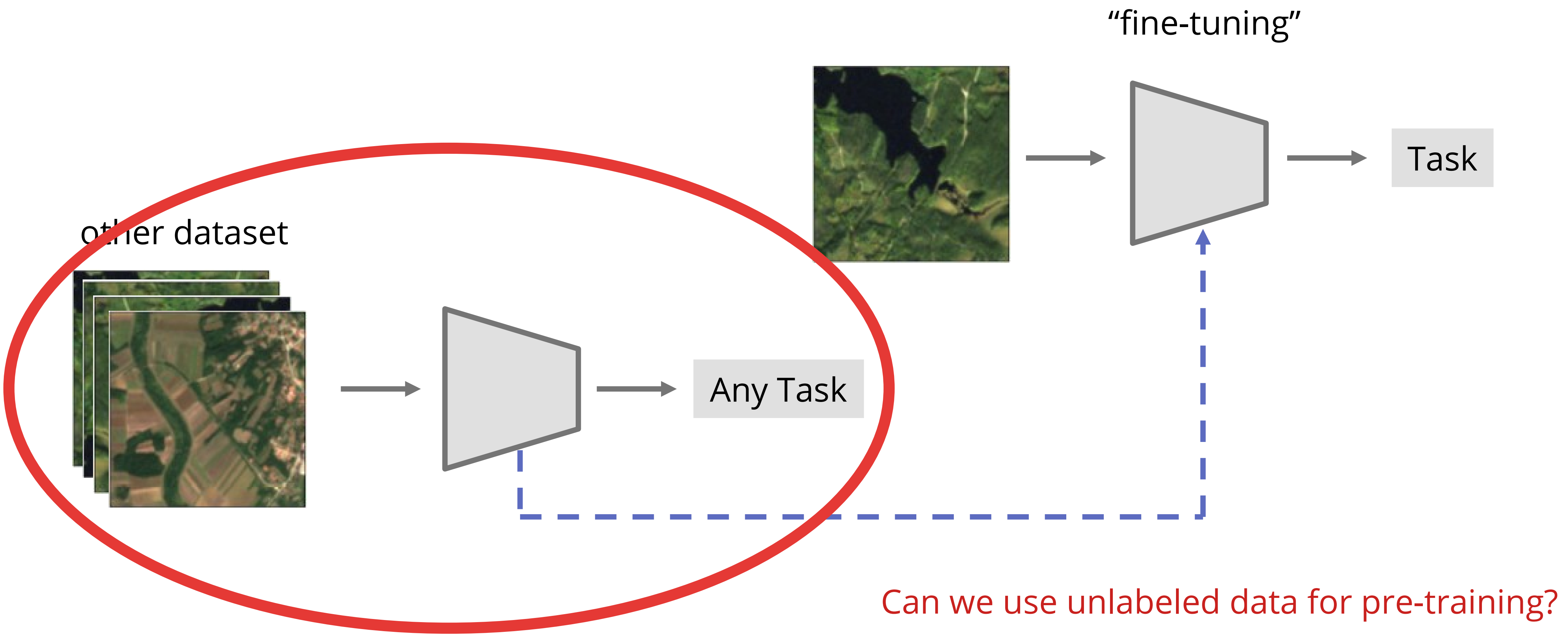


We initialize our model with the **pre-trained** model weights; training starts not from scratch!

In the end, transfer learning simply means that your model has previously been trained: you load a model checkpoint and resume training on your data and for your downstream task.

Implementing Transfer Learning is simple. Let’s do it!

Transfer Learning still needs labels



Can we use unlabeled data for pre-training?

Self-Supervised Learning (SSL) and Transfer Learning

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Self-supervised learning: learn “to see”, differentiate between image features (edges, colors) without supervision

Self-Supervised Learning (SSL) and Transfer Learning

Self-supervised learning: learn "to see", differentiate between image features (edges, colors) without supervision

Transfer learning: use the learned features to solve a task by providing "few labels"

Contrastive self-supervised learning

Contrastive learning setup (following SimCLR):

Chen, Ting, Simon Kornblith, Mohammad Norouzi and Geoffrey E. Hinton. “A Simple Framework for Contrastive Learning of Visual Representations.” ArXiv abs/2002.05709 (2020)

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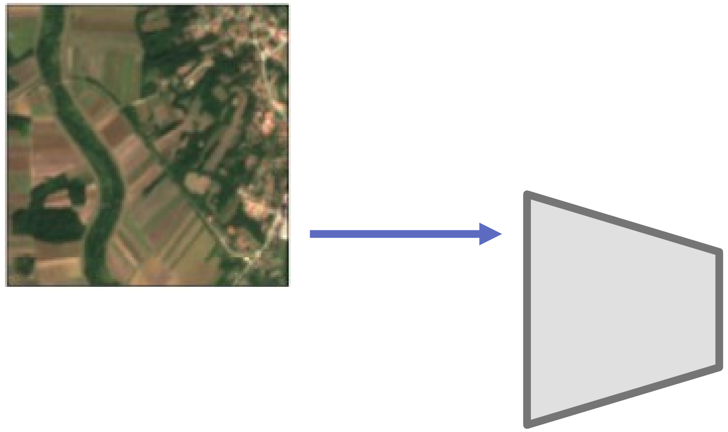

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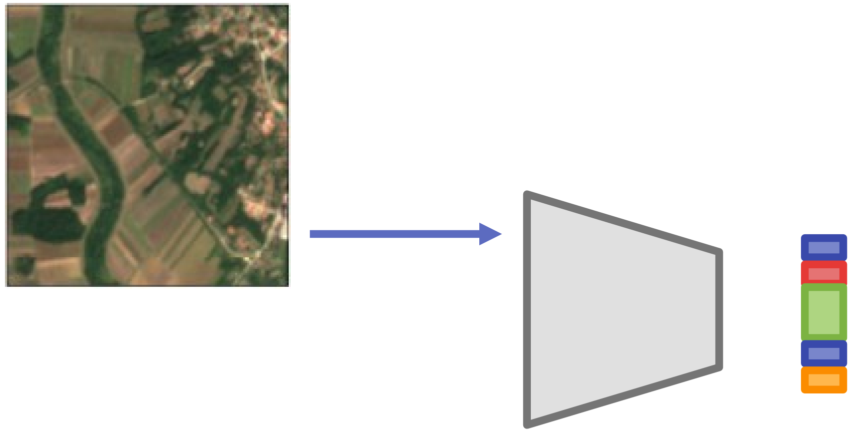

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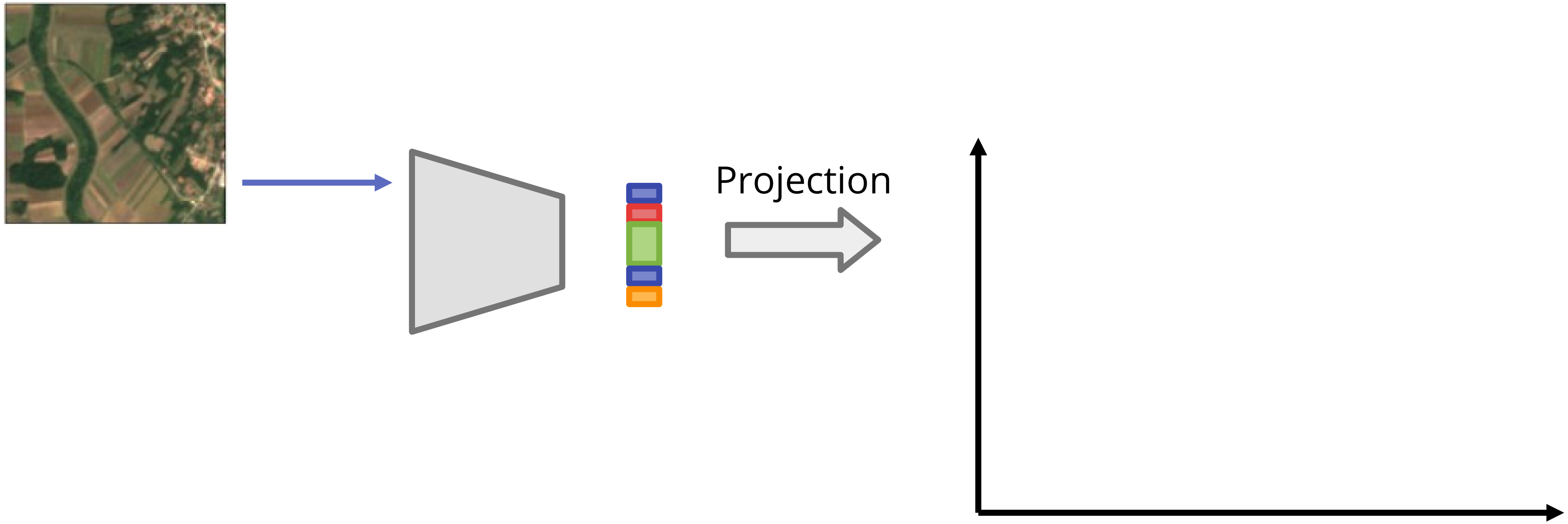

“n-dim latent space”

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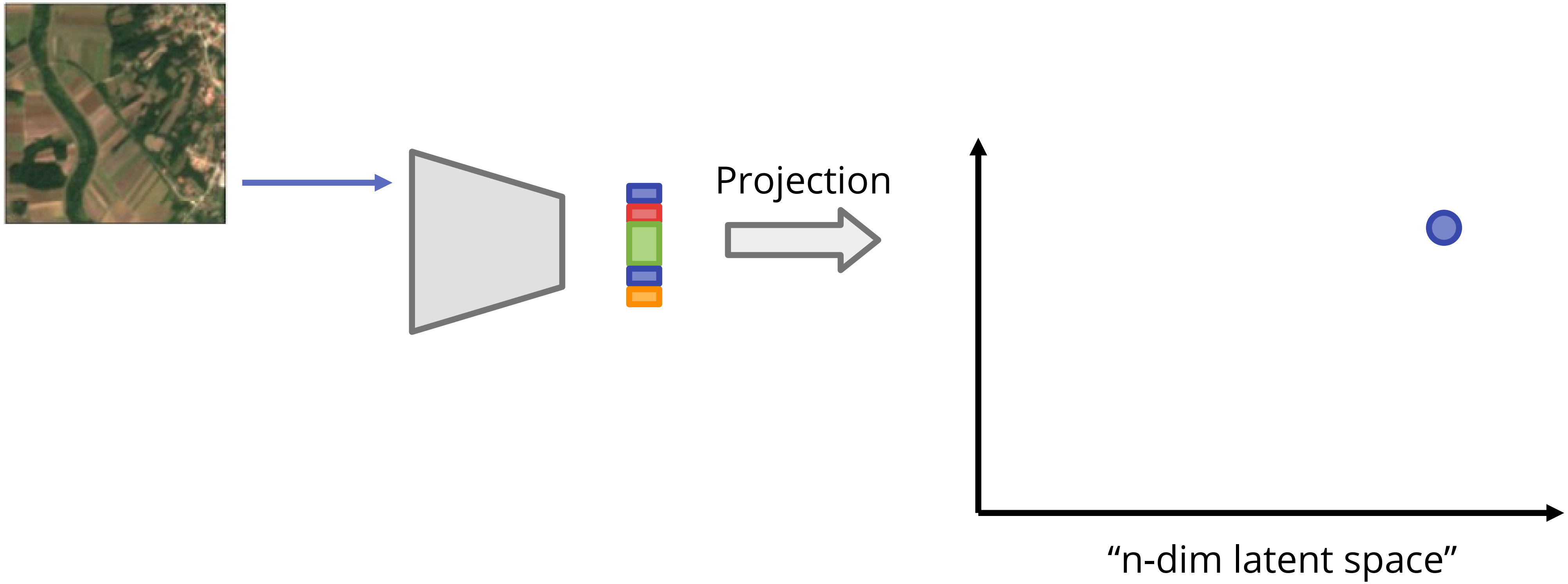

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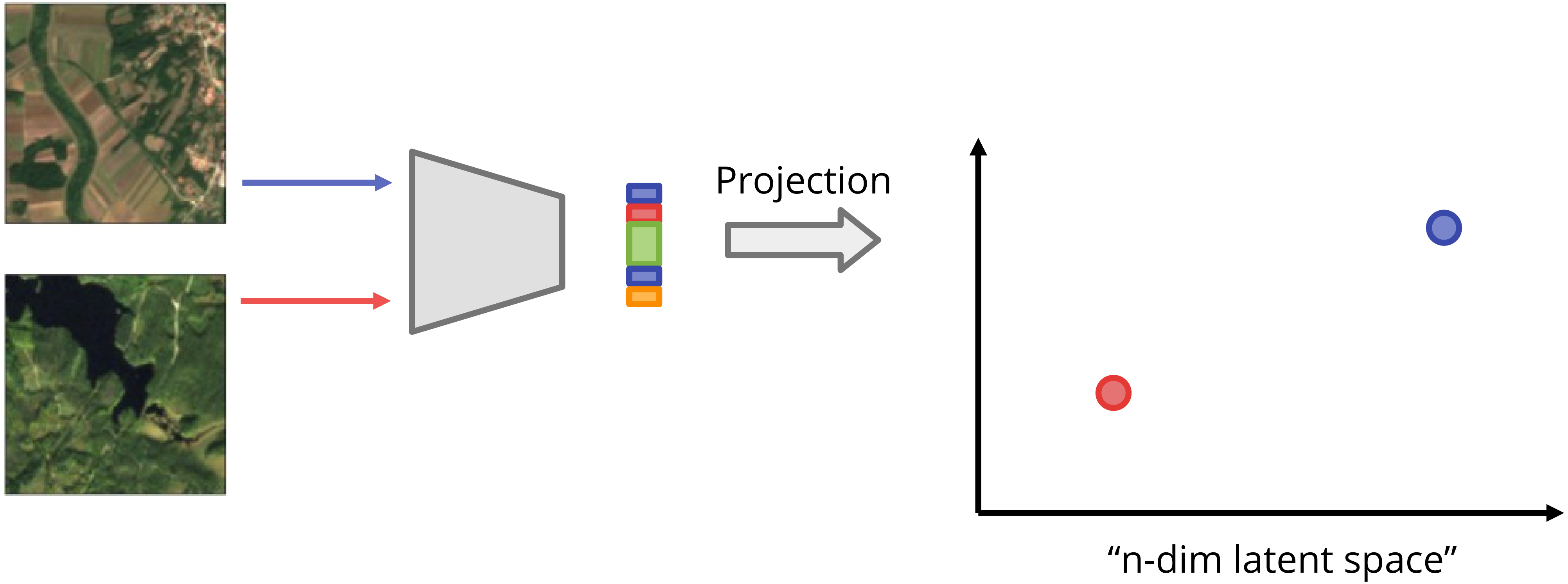

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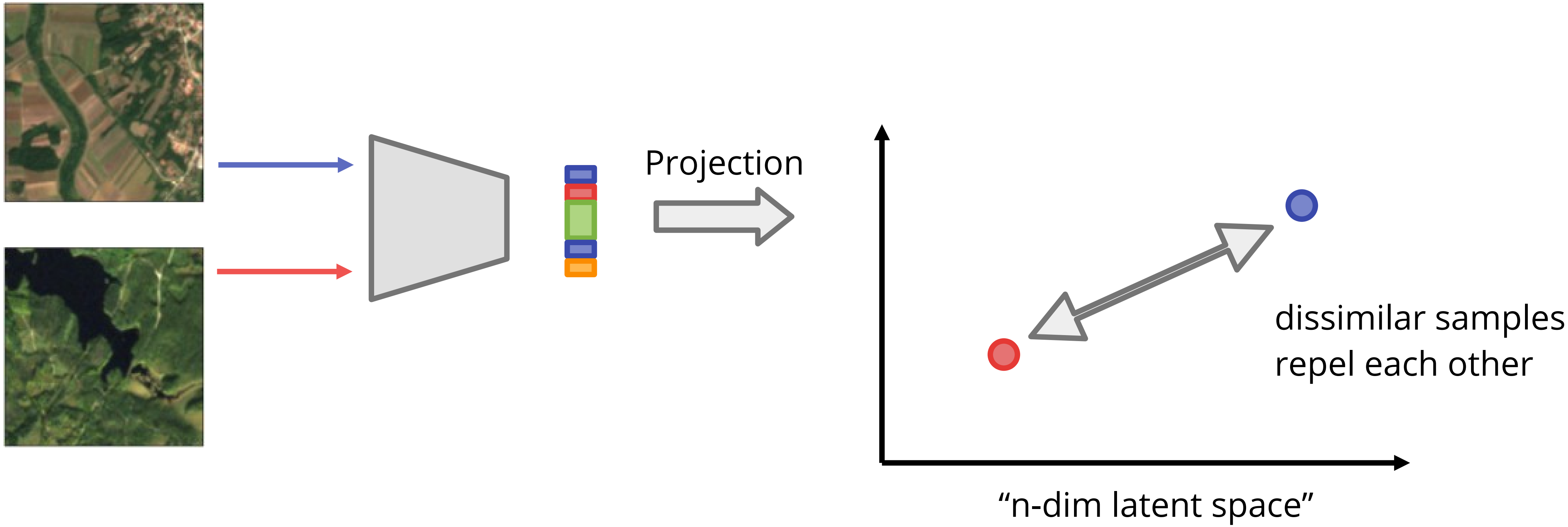

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Contrastive self-supervised learning

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

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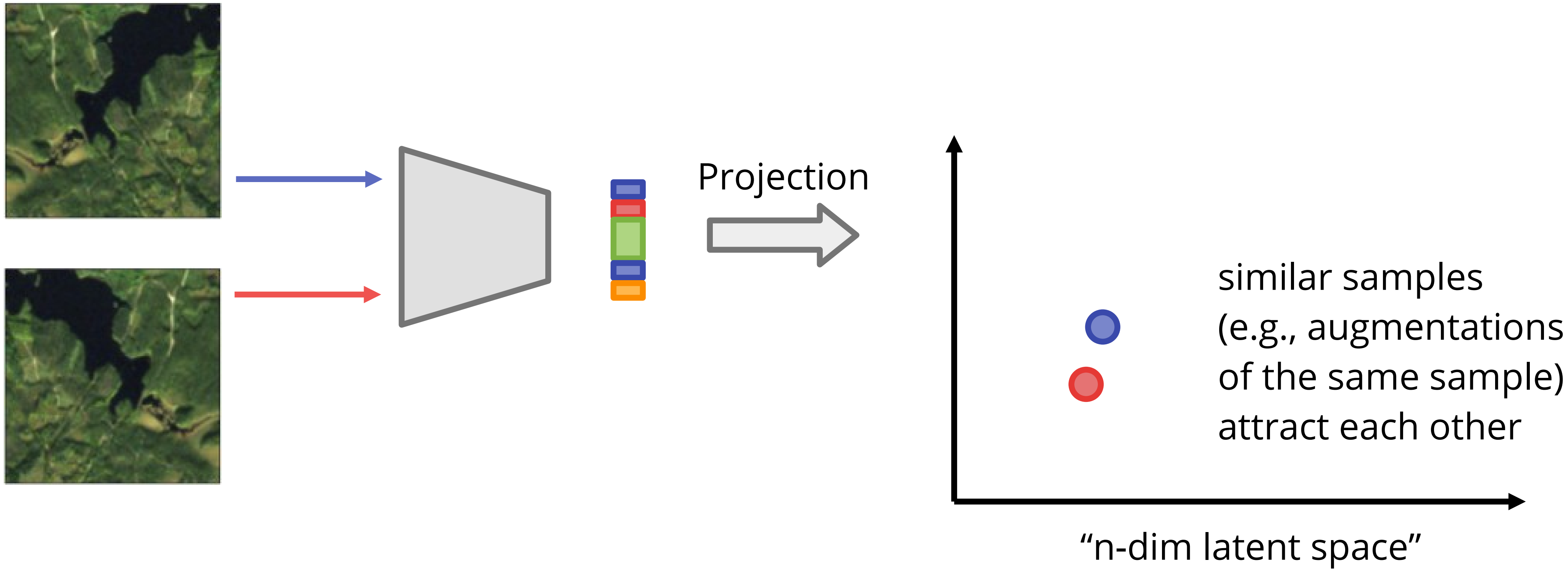

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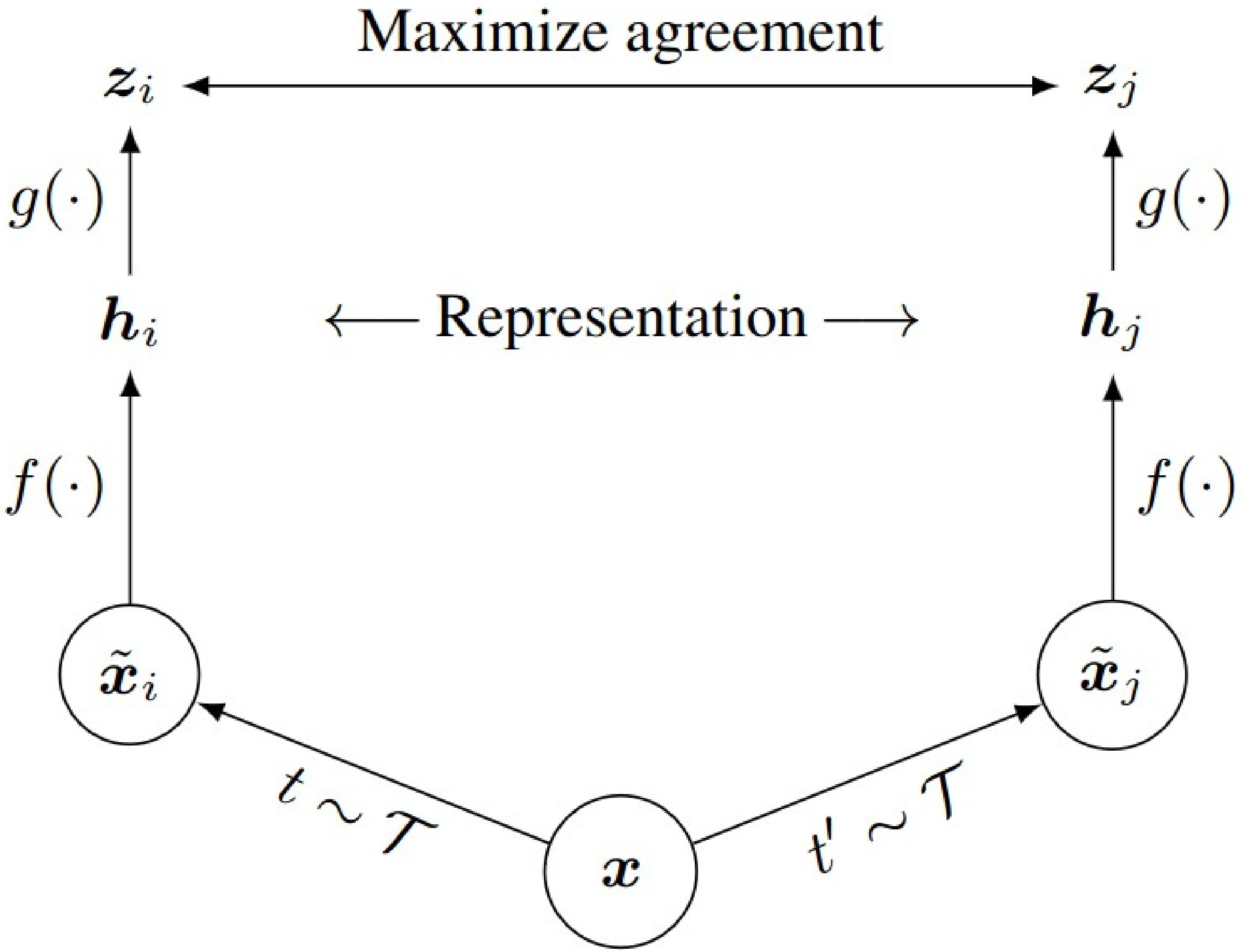
SimCLR: A Simple Framework for Contrastive Learning of Visual Representations



Chen et al. (2020)

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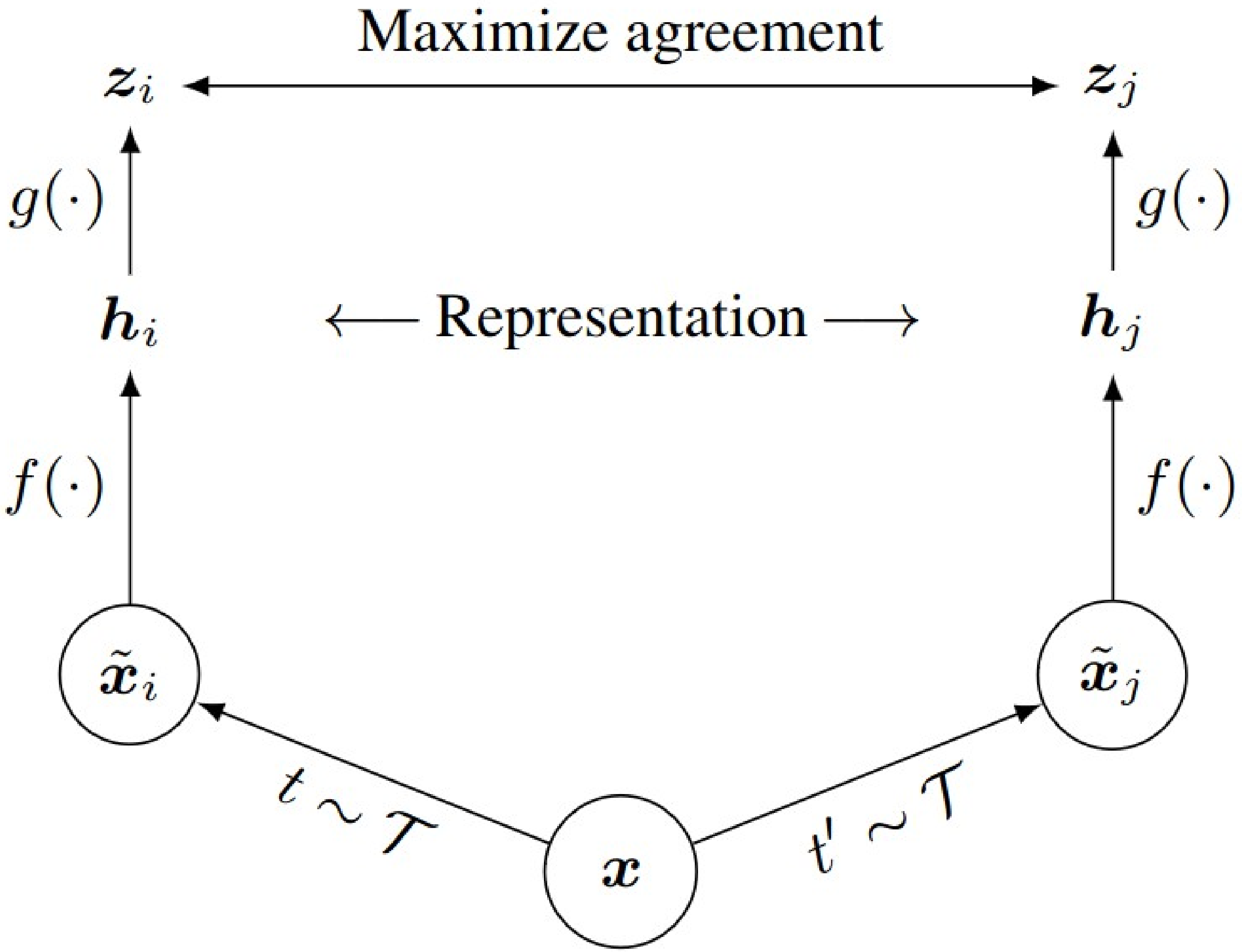

Data augmentations (Transformations) are key for SimCLR to work.

Chen et al. (2020)

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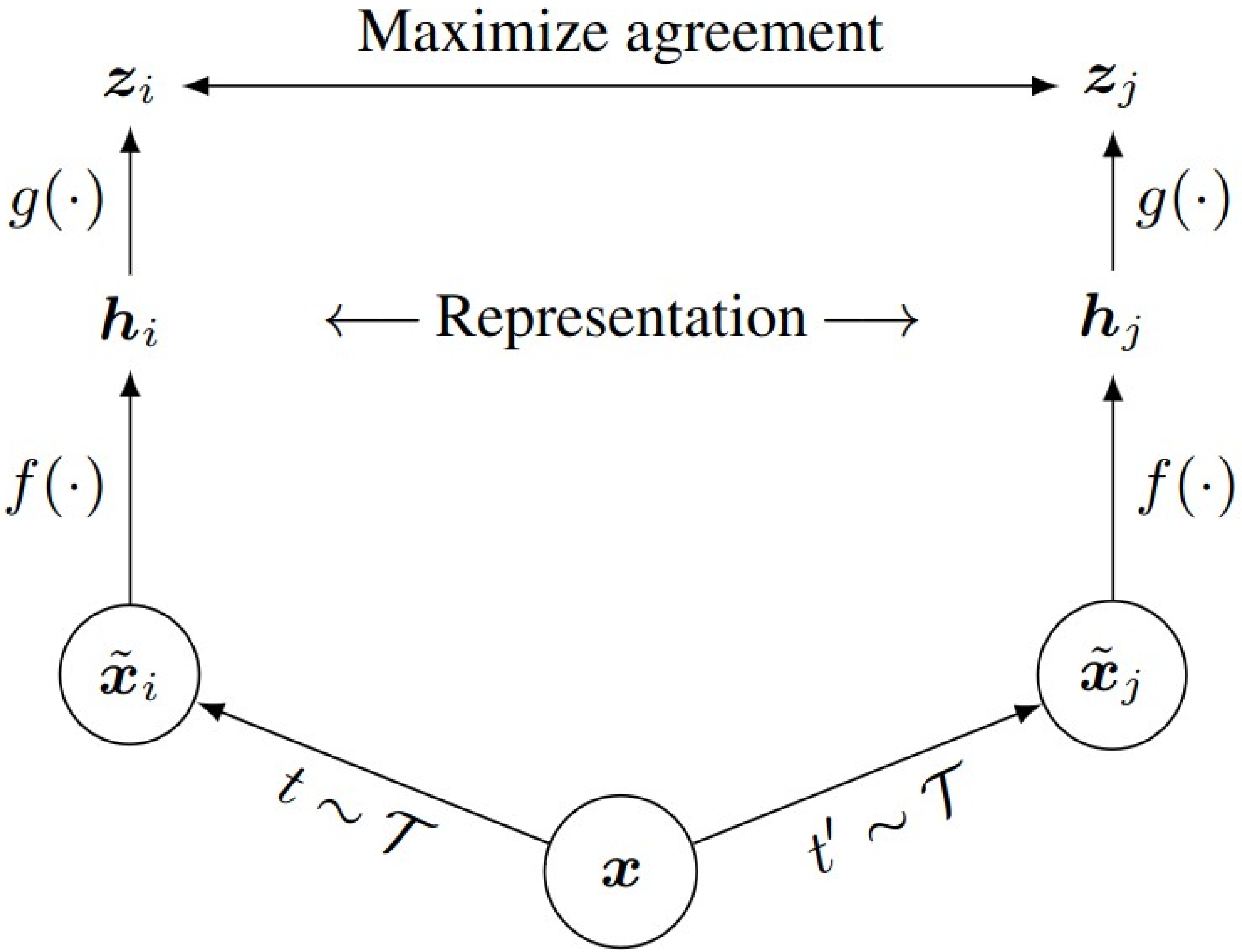
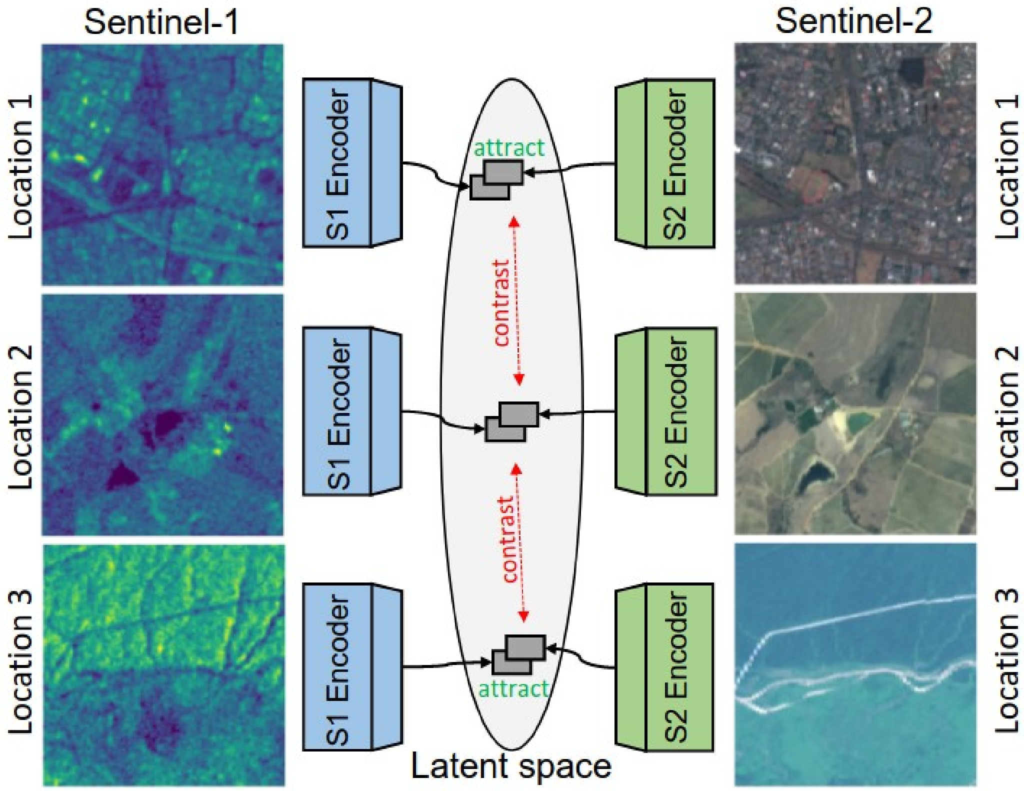


Data augmentations (Transformations) are key for SimCLR to work.

In remote sensing, we naturally have different views of the same scence (different times, different data modalities, etc.) We can leverage these views…

Chen et al. (2020)

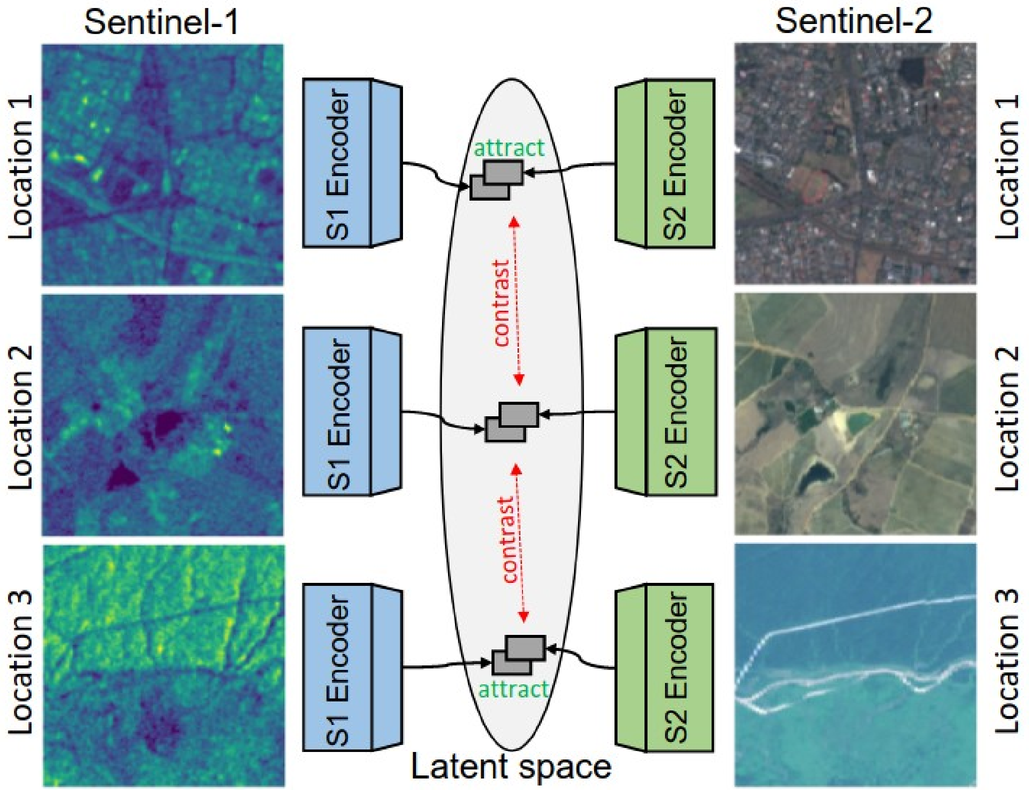
Contrastive SSL for Earth observation: an Example



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

Contrastive SSL for Earth observation: an Example

Pre-training



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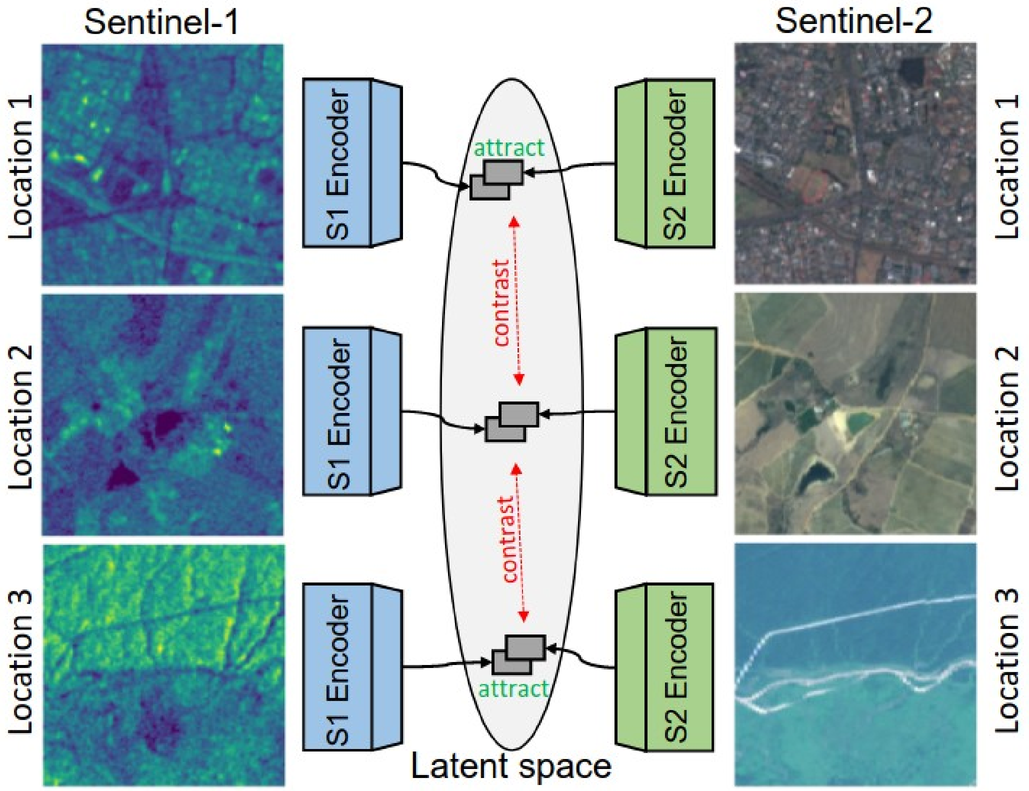
Contrastive SSL for Earth observation: an Example

Pre-training

- Multimodal dataset (SEN12MS, ~181k Sentinel-1/2 patch pairs)



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Contrastive SSL for Earth observation: an Example

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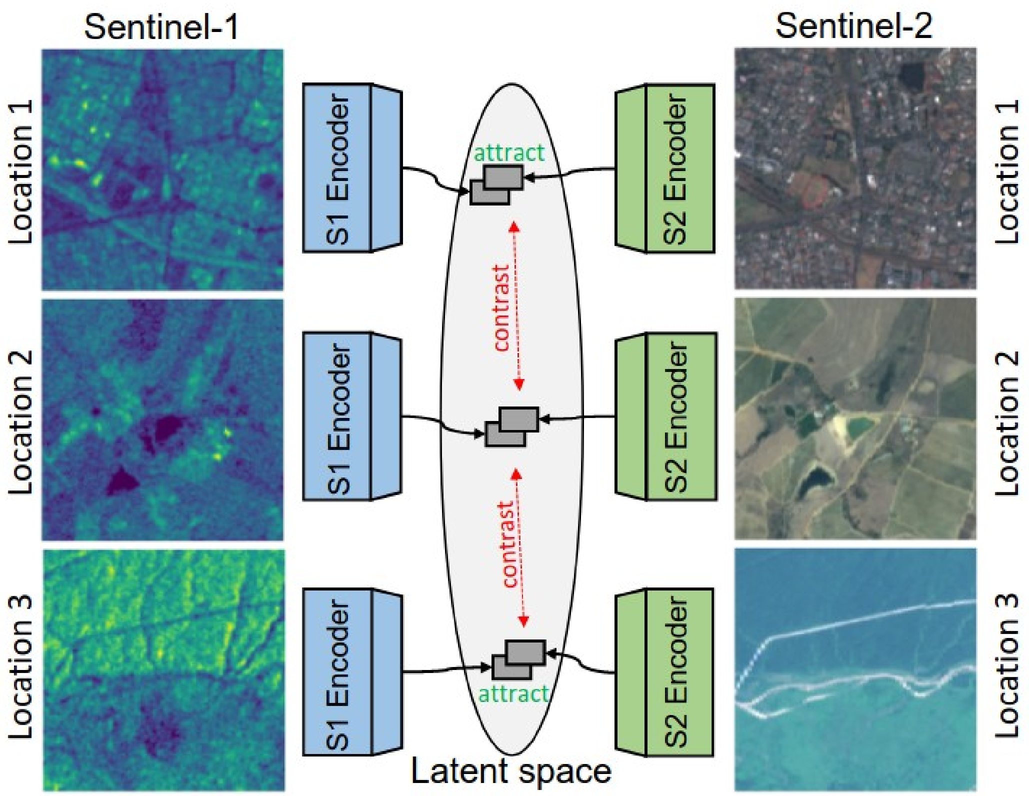
- Separate backbones for each modality



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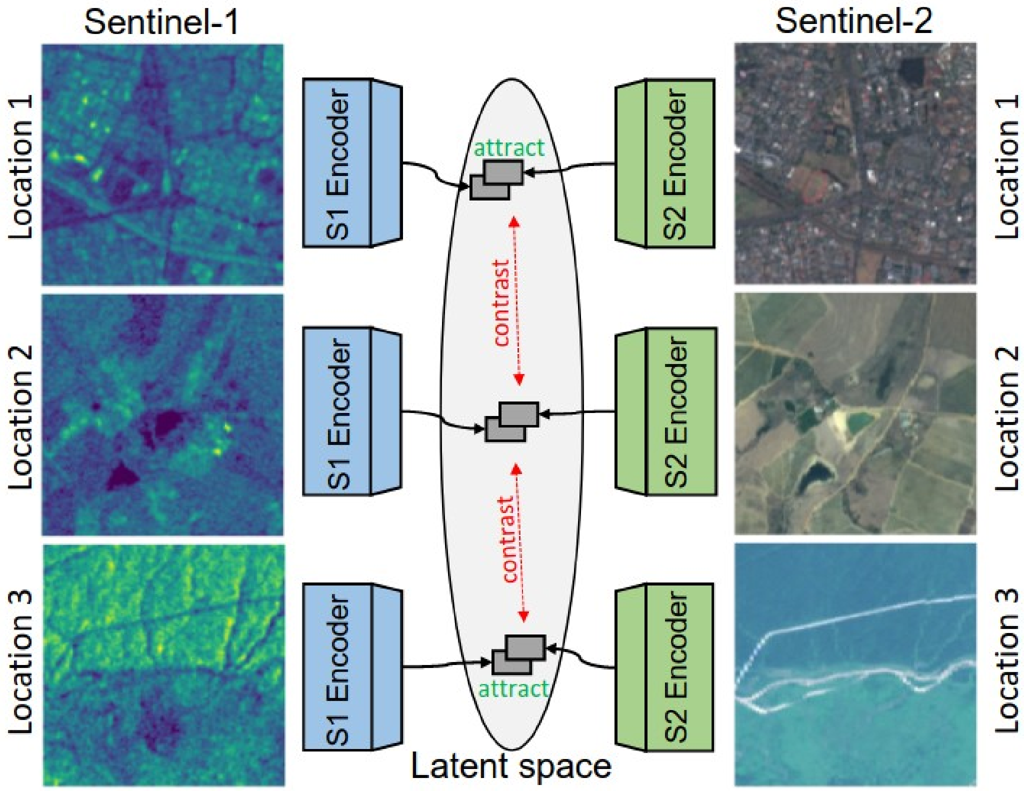
Pre-training

- Multimodal dataset (SEN12MS, ~181k Sentinel-1/2 patch pairs)
- Separate backbones for each modality
- Augmentation-free, contrastive setup



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Let’s see how we can build this architecture…

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Contrastive SSL for Earth observation: an Example

Fine-tuning on classification task

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Contrastive SSL for Earth observation: an Example

Fine-tuning on classification task

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

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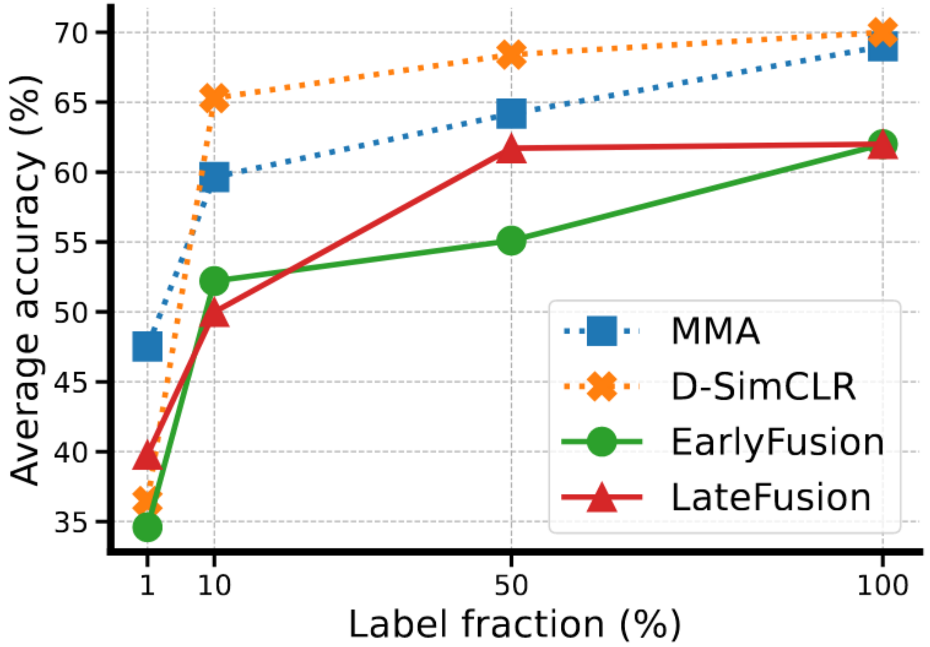

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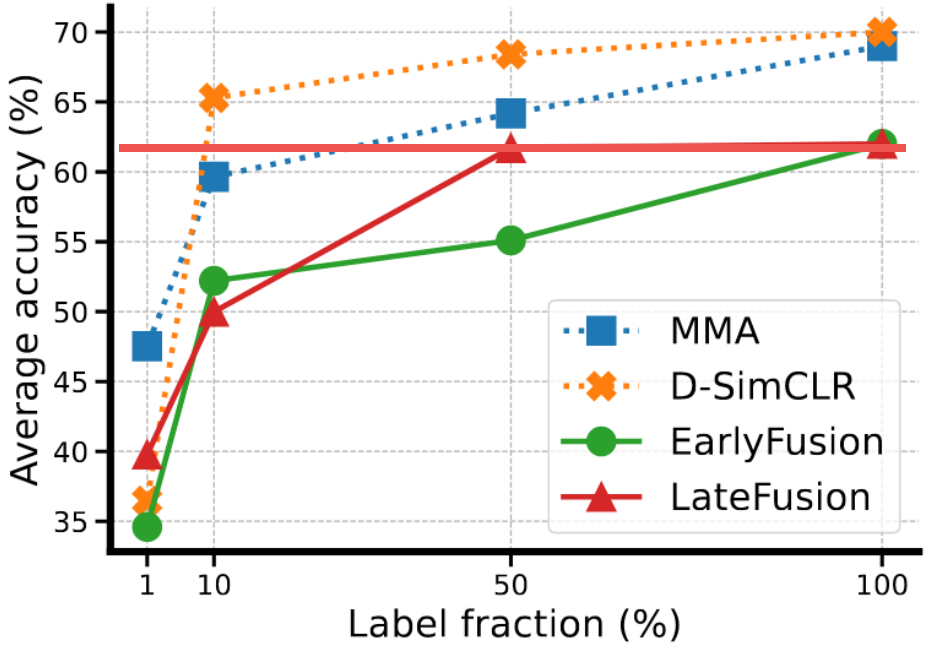

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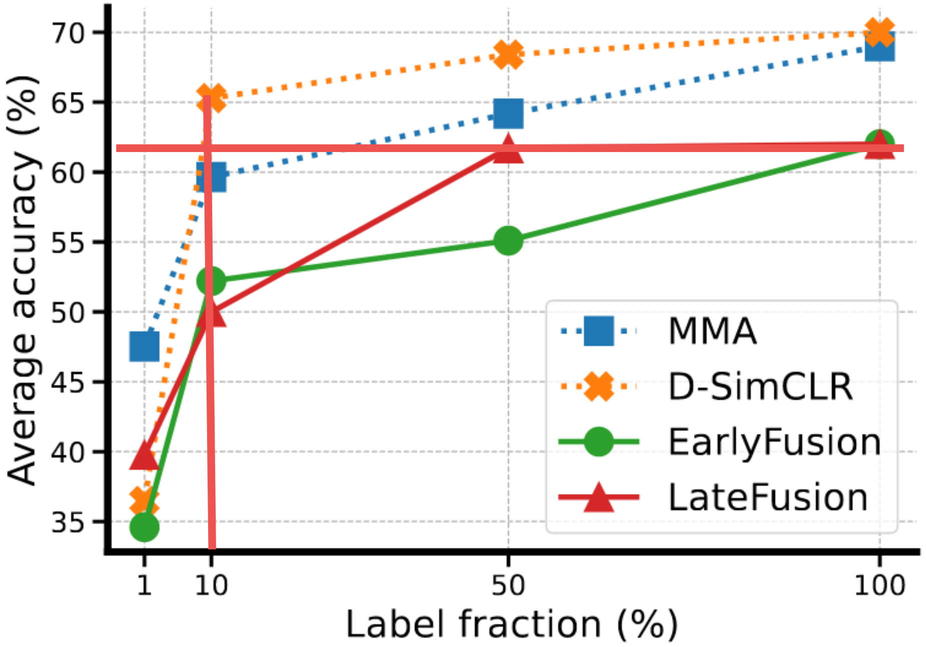

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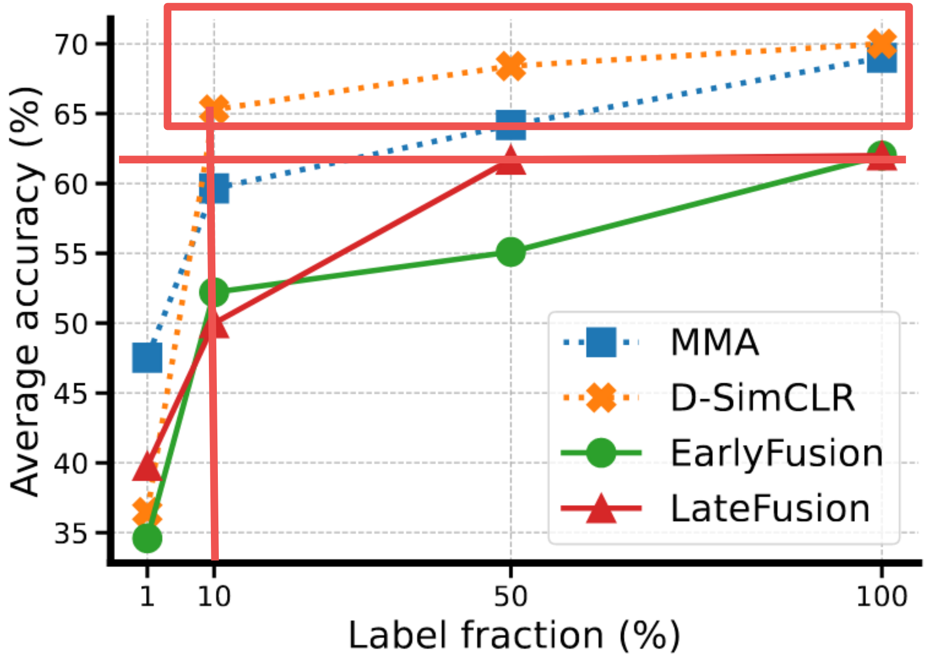

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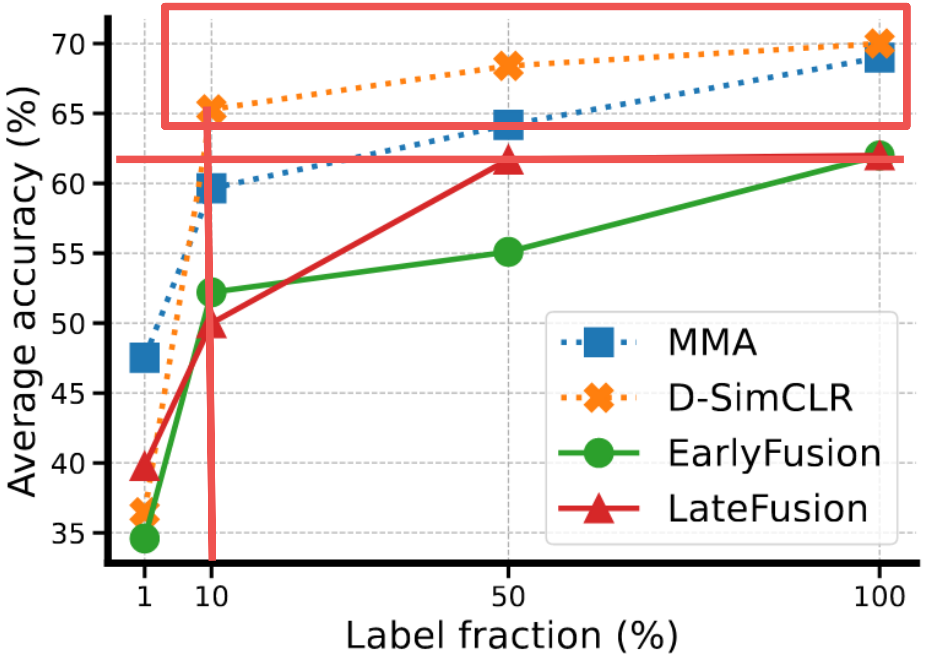
Contrastive SSL for Earth observation: an Example

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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This is it!

Summary

We introduced a number of methods to make more efficient use of labels (or use no labels at all):

- Data augmentations
- Data Fusion
- Multi-task Learning
- Transfer Learning
- Self-supervised Learning

Now go out into the world and use the code that we discussed for your own research!