Data-efficient Deep Learning for Earth Observation

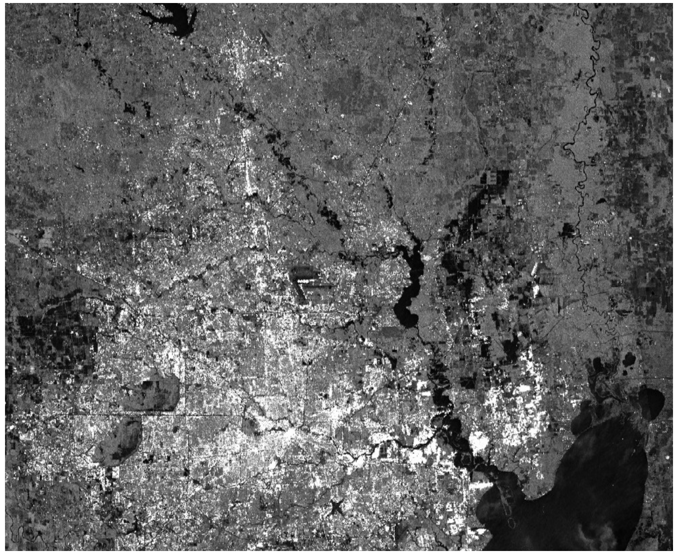
Deep Learning Recap

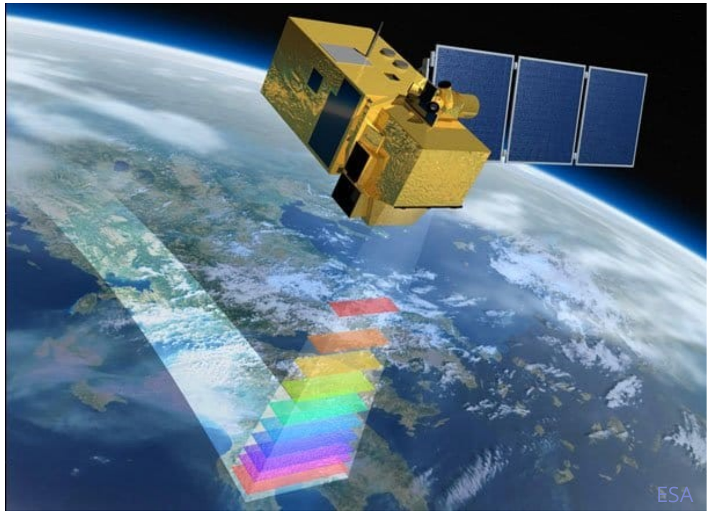
Michael Mommert

Deep Learning for Earth observation

Deep Learning for Earth observation

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

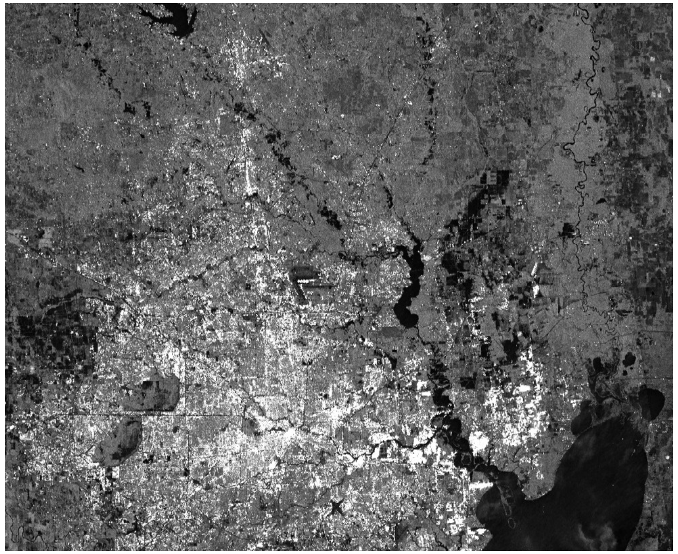


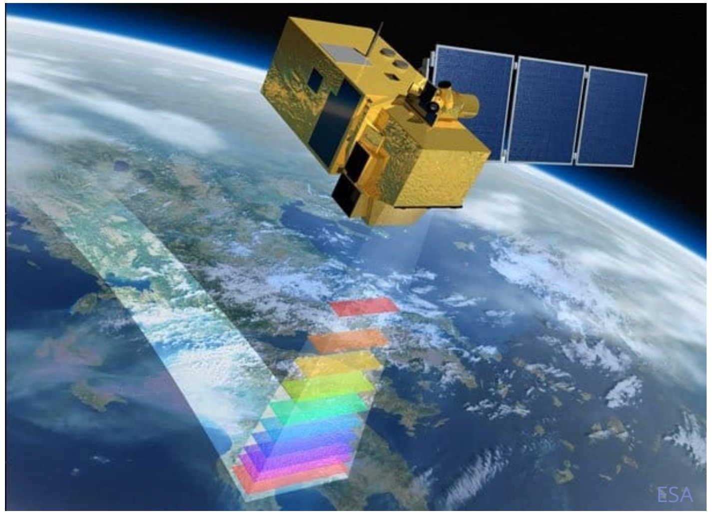


Deep Learning for Earth observation

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

How can we analyze these vast amounts of data?



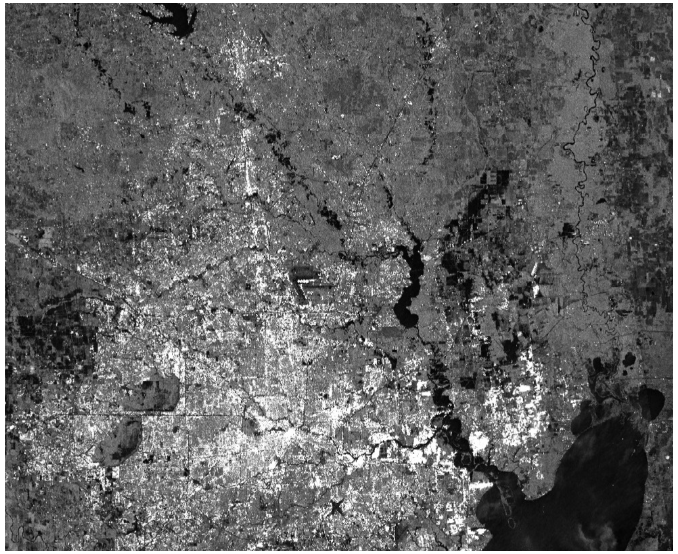


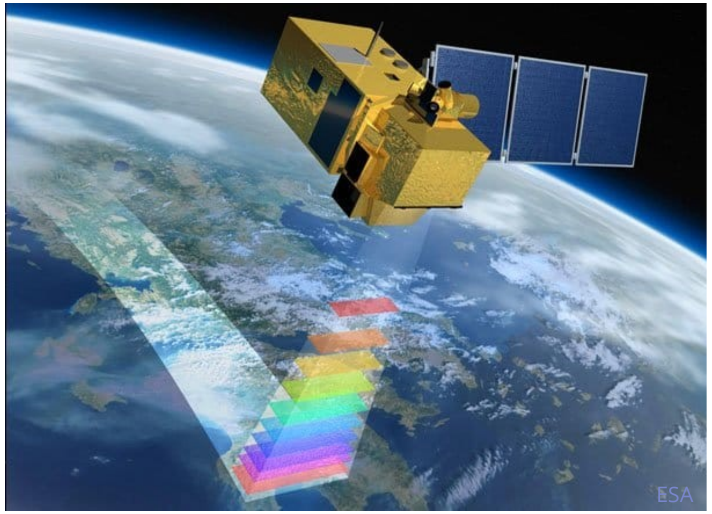
Deep Learning for Earth observation

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

How can we analyze these vast amounts of data?

Deep Learning offers the **scalability** to analyze large amounts of data.





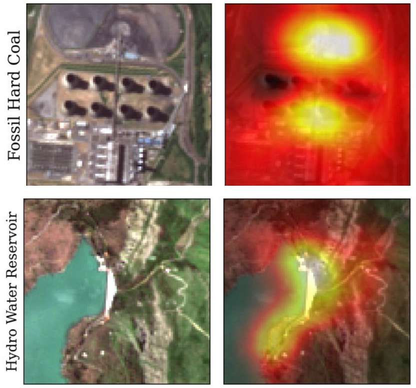
Deep Learning for Earth observation

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

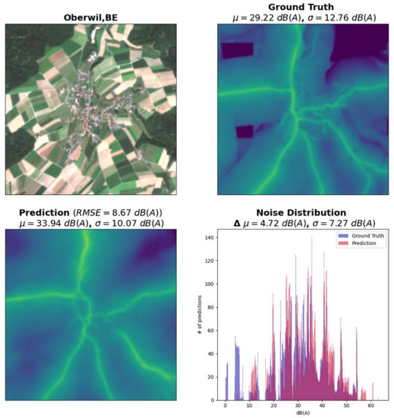
How can we analyze these vast amounts of data?

Deep Learning offers the **scalability** to analyze large amounts of data.

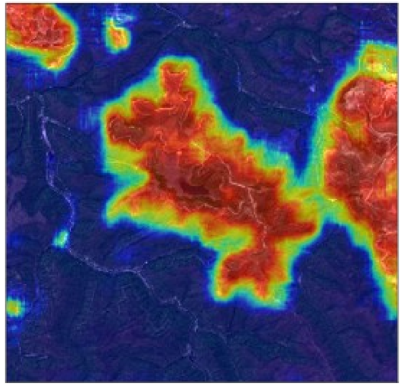
Deep Learning also offers the **flexibility** to deal with a range of different tasks.



Classification



Regression



Segmentation

Object Detection

Deep Learning for Earth observation

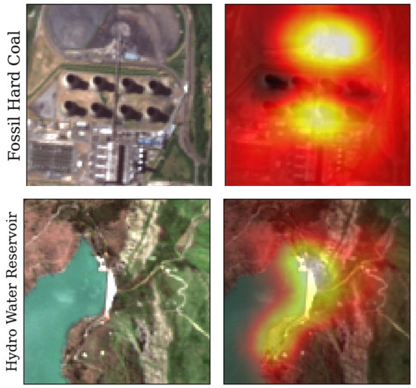
Earth observation data are highly complex (unstructured, multi-modal).

How can we analyze these vast amounts of data?

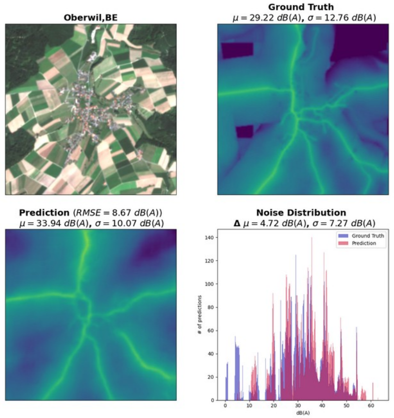
Deep Learning offers the **scalability** to analyze large amounts of data.

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

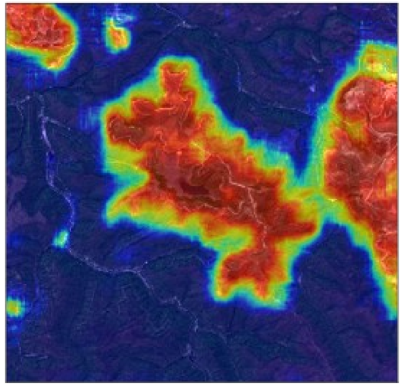
How does it work?



Classification



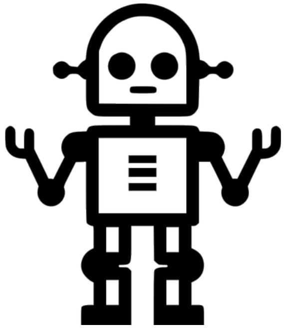
Regression



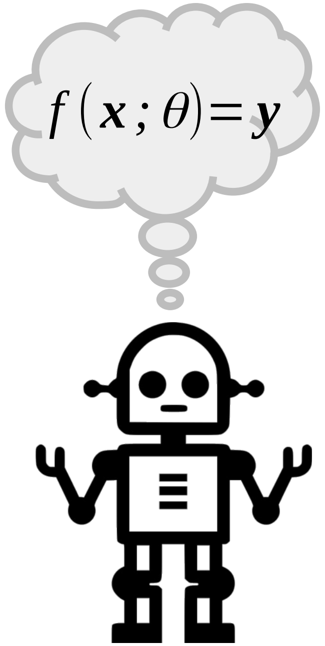
Segmentation

Object Detection

Supervised learning with Neural Networks



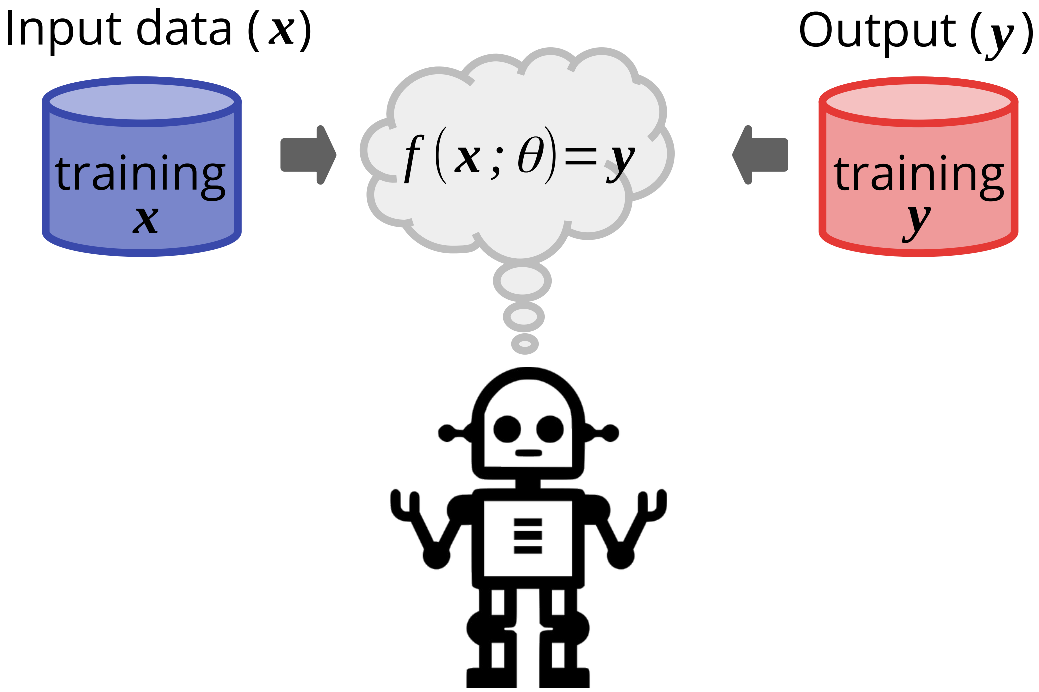
Supervised learning with Neural Networks



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

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

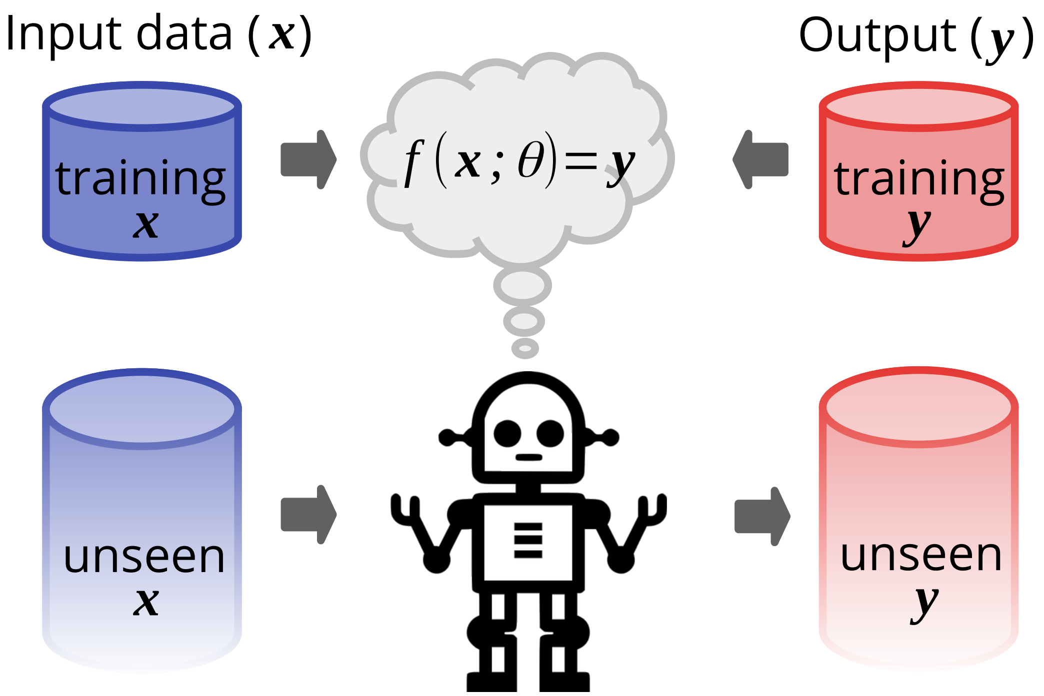
Supervised learning with Neural Networks



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

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

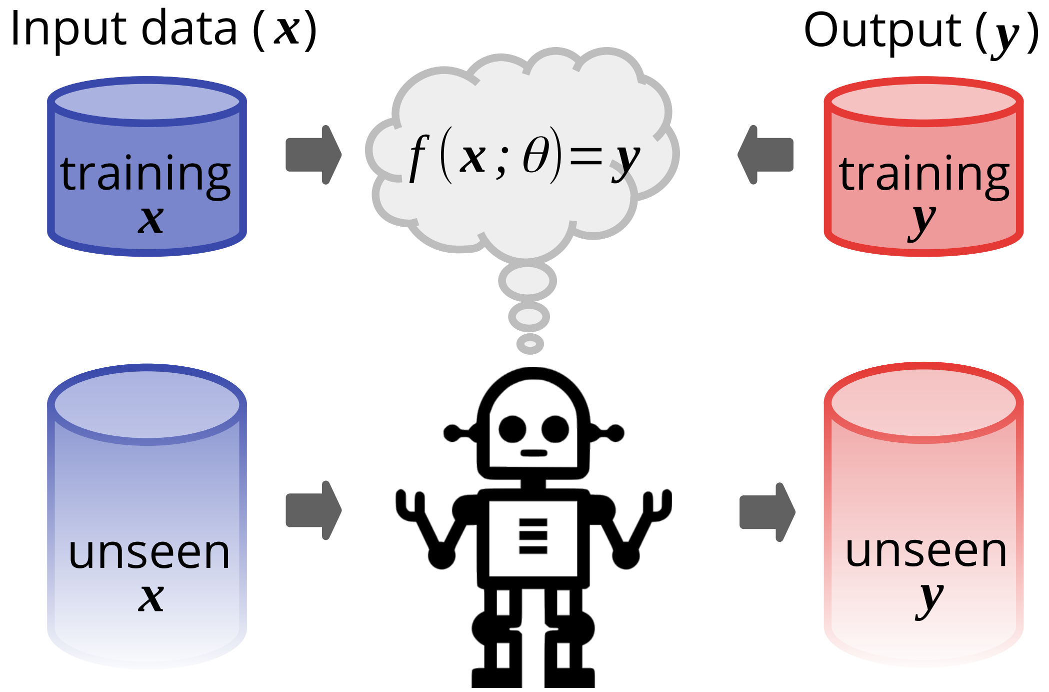
Supervised learning with Neural Networks

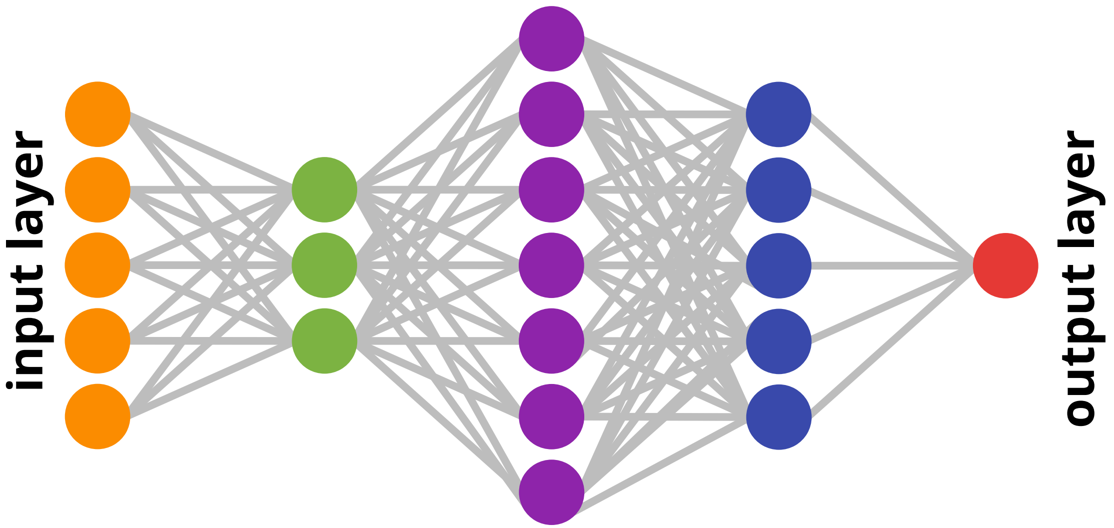


A machine learns a task from **annotated examples**.

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

Supervised learning with Neural Networks



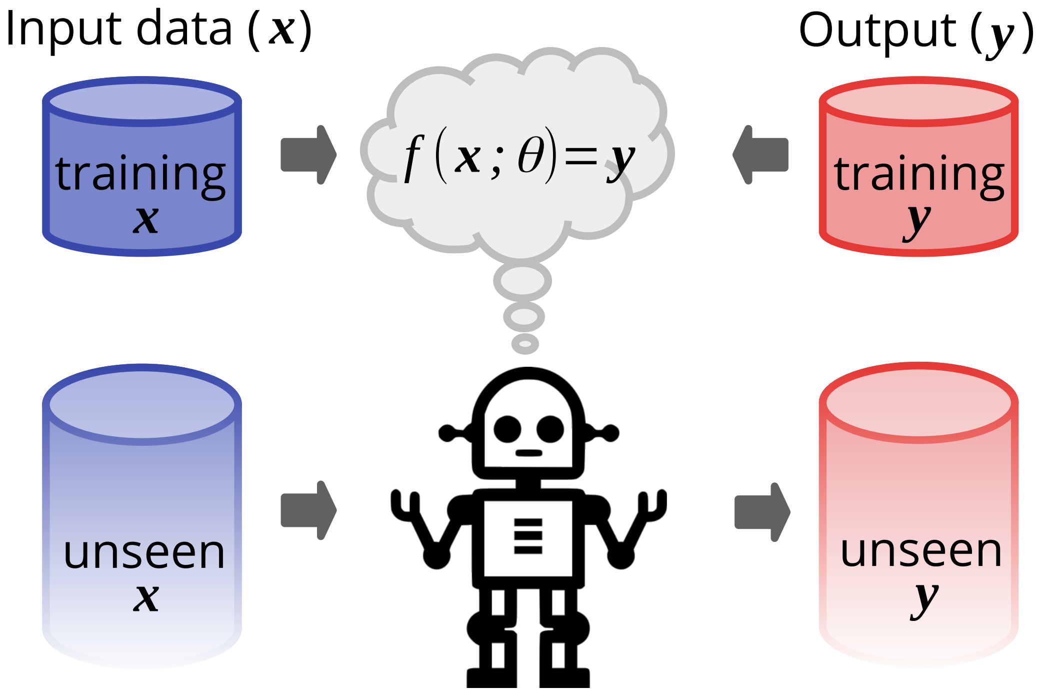


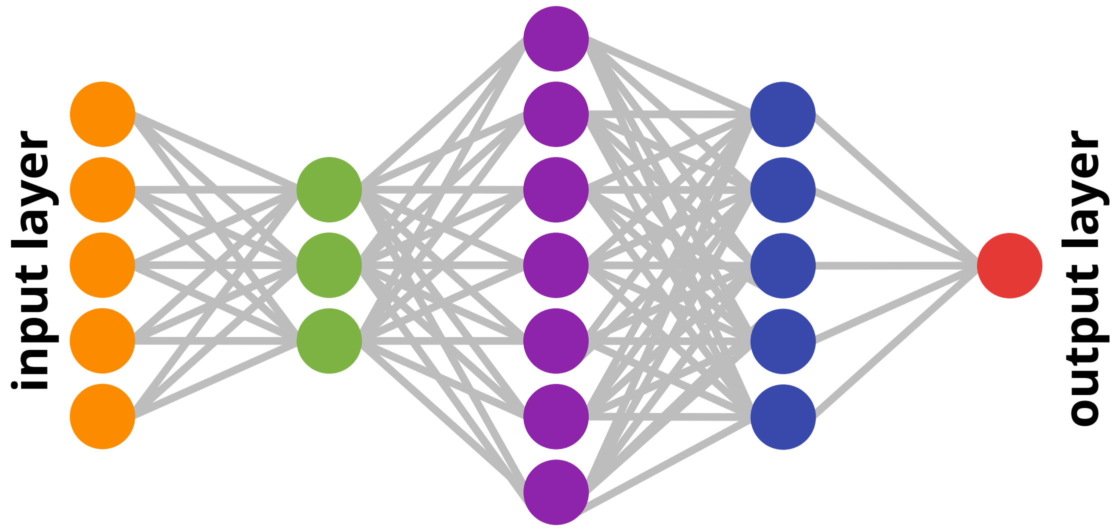
A machine learns a task from **annotated examples**.

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

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

Supervised learning with Neural Networks





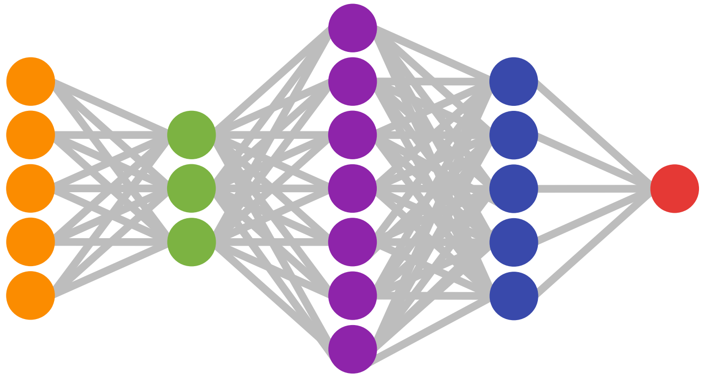
A machine learns a task from **annotated examples**.

Mathematically, it learns a function, f, that maps input data, x, to the output, y.

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

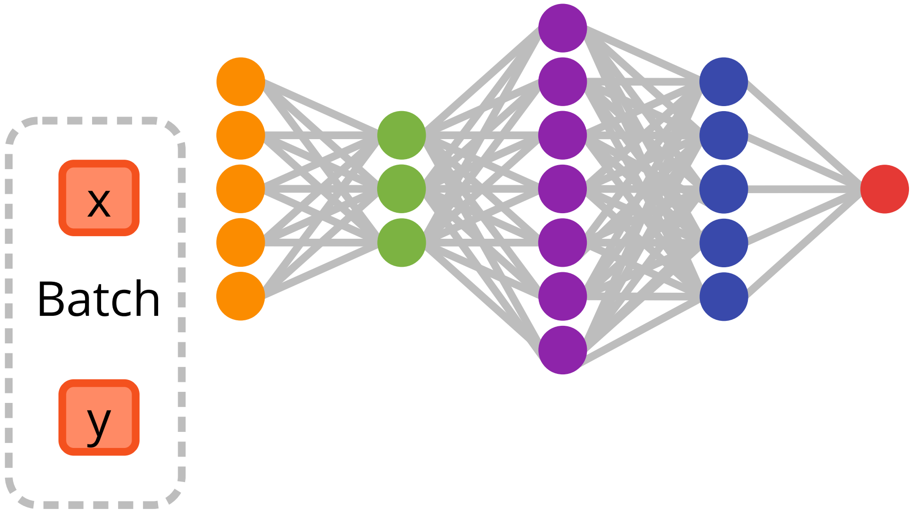
How does the model learn?

Neural network training pipeline



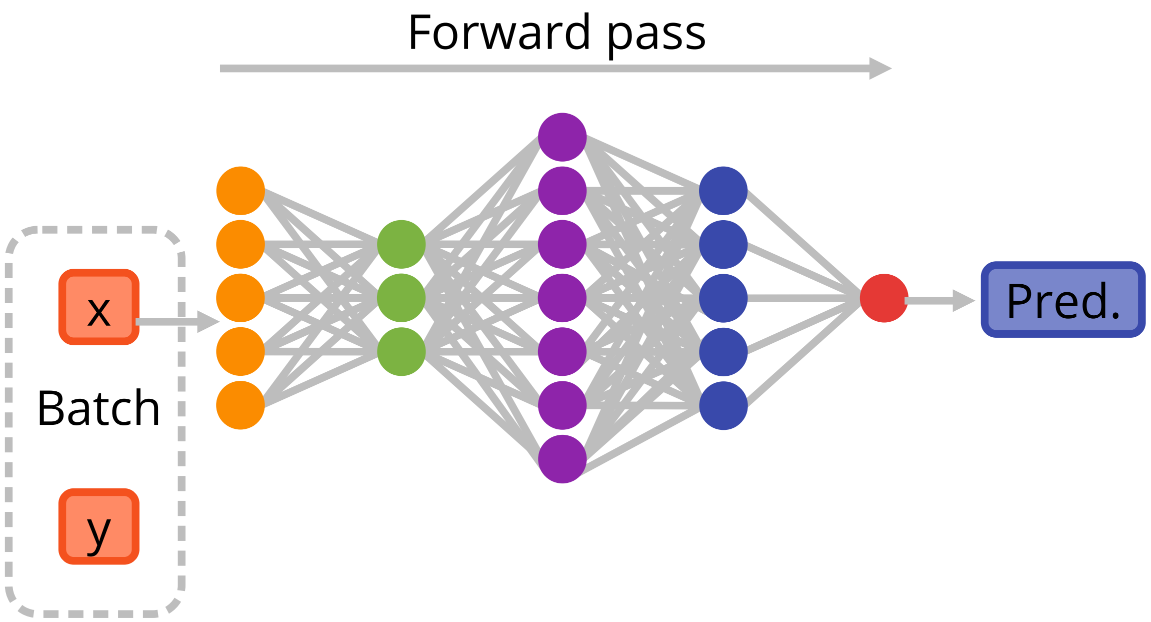
Neural network training pipeline

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



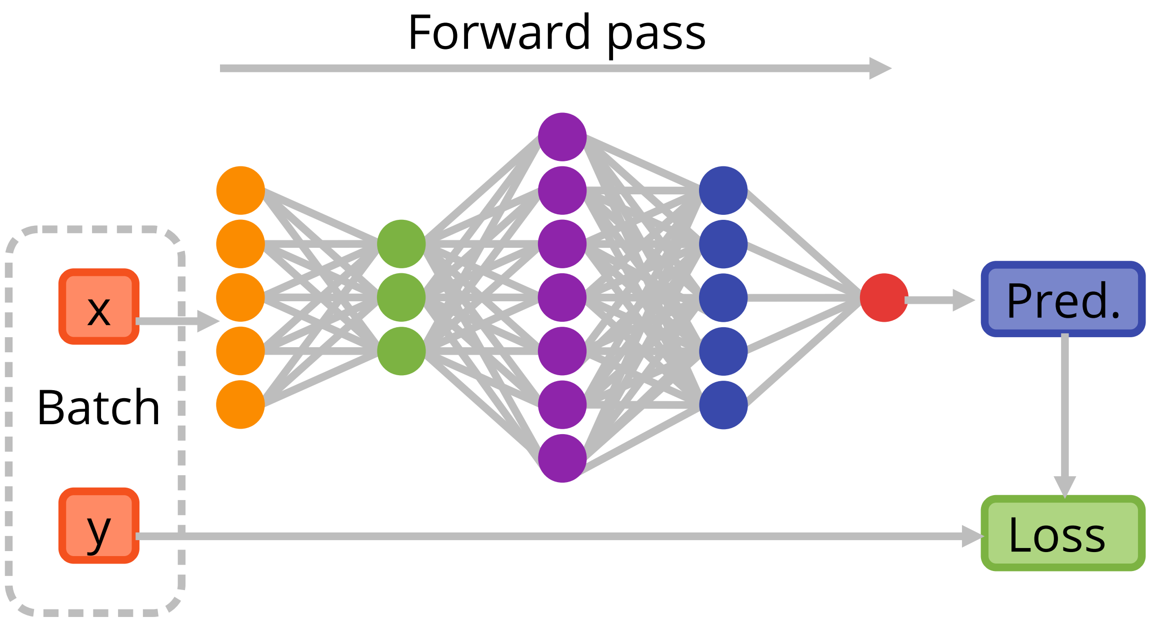
Neural network training pipeline

- Sample batch (input data x and target data y) from training dataset:
  - Evaluate model on batch input data (=prediction) in forward pass



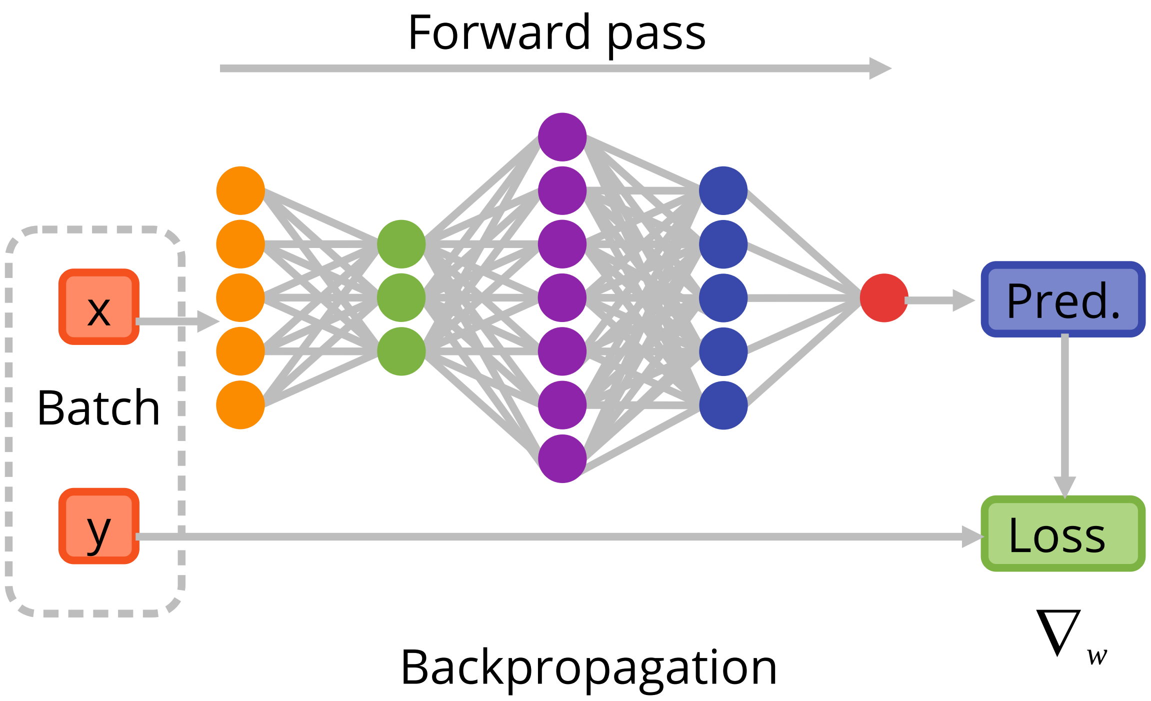
Neural network training pipeline

- Sample batch (input data x and target data y) from training dataset:
  - Evaluate model on batch input data (=prediction) in forward pass
  - Compute loss on prediction and target y



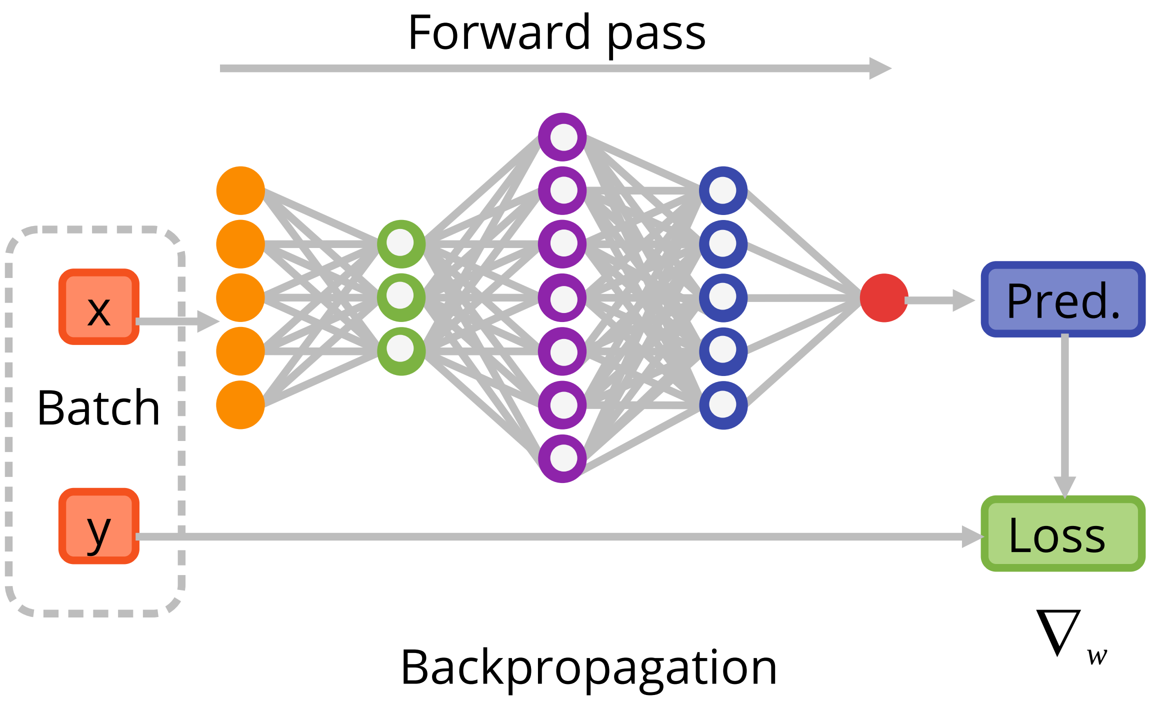
Neural network training pipeline

- Sample batch (input data x and target data y) from training dataset:
  - Evaluate model on batch input data (=prediction) in forward pass
  - Compute loss on prediction and target y
  - Compute weight gradients with backprop.



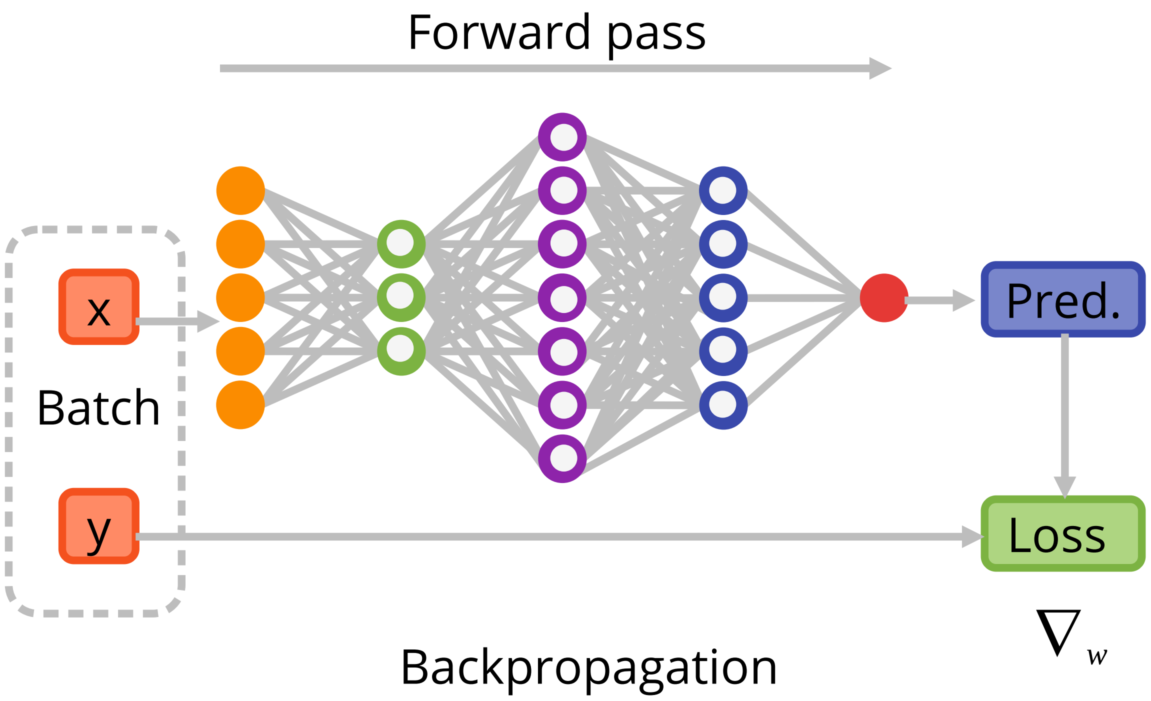
Neural network training pipeline

- Sample batch (input data x and target data y) from training dataset:
  - Evaluate model on batch input data (=prediction) in forward pass
  - Compute loss on prediction and target y
  - Compute weight gradients with backprop.
  - Modify weights based on gradients and learning rate



Neural network training pipeline

- Sample batch (input data x and target data y) from training dataset:
  - Evaluate model on batch input data (=prediction) in forward pass
  - Compute loss on prediction and target y
  - Compute weight gradients with backprop.
  - Modify weights based on gradients and learning rate
  - Repeat for all batches



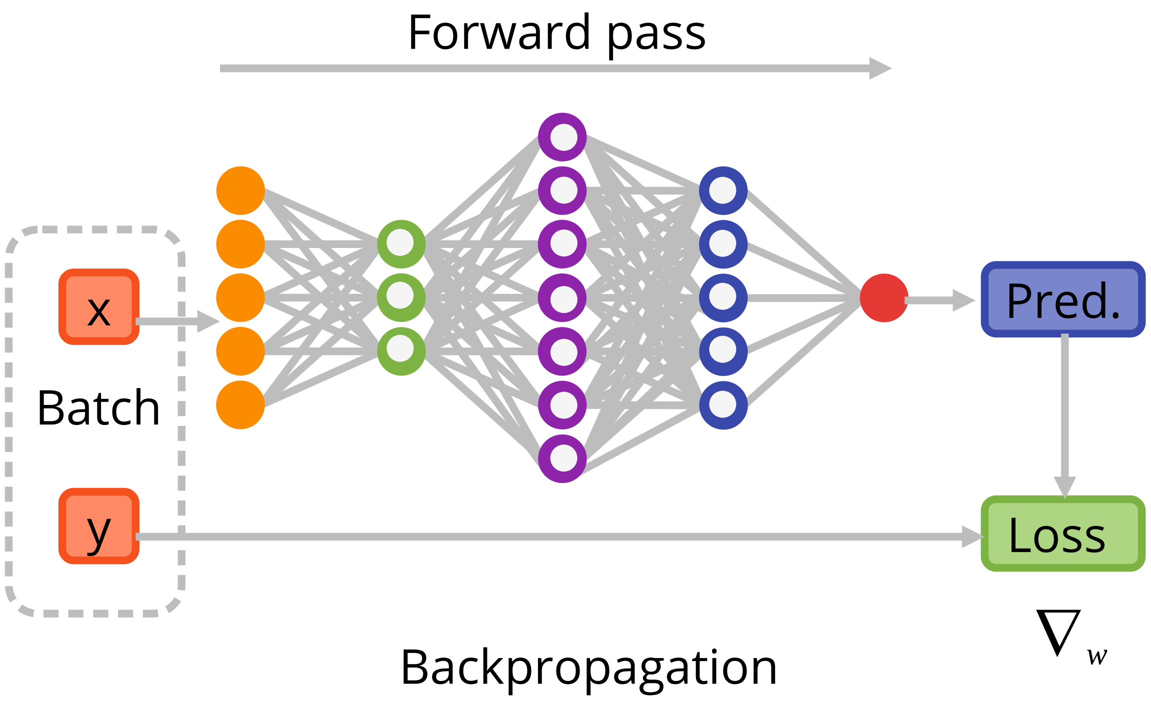
Neural network training pipeline

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

1 epoch

  - Evaluate model on batch input data (=prediction) in forward pass
  - Compute loss on prediction and target y
  - Compute weight gradients with backprop.
  - Modify weights based on gradients and learning rate
  - Repeat for all batches

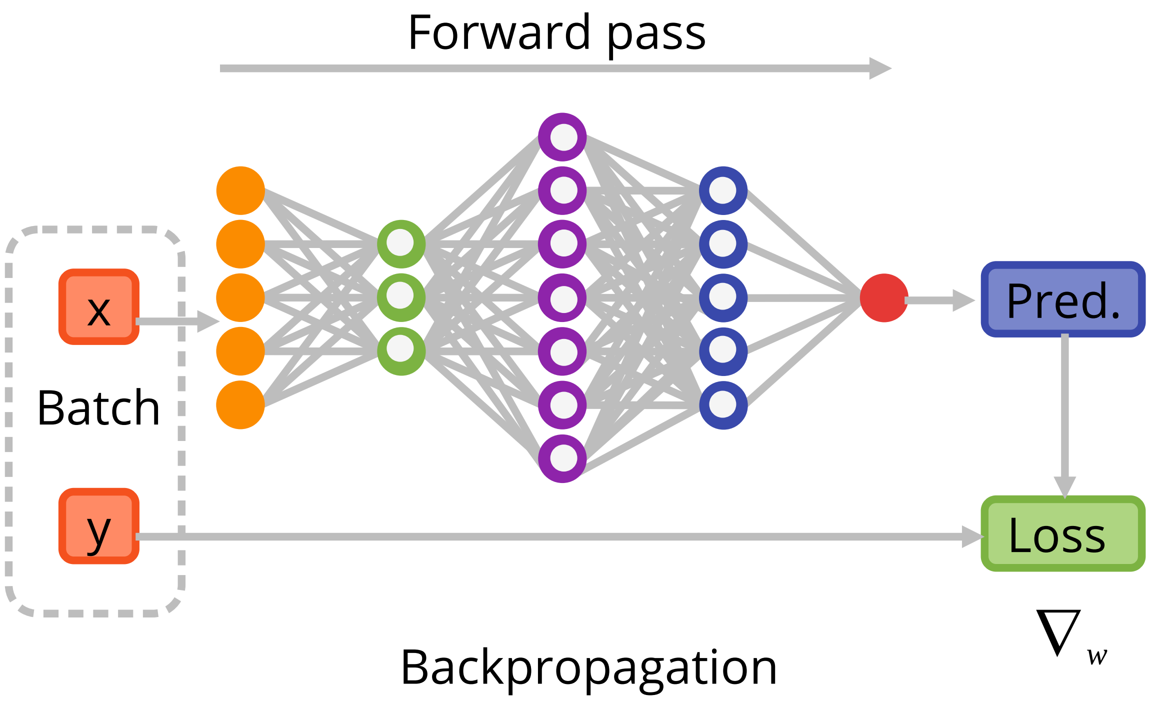
- Repeat for a number of epochs, monitor training and validation loss + metrics



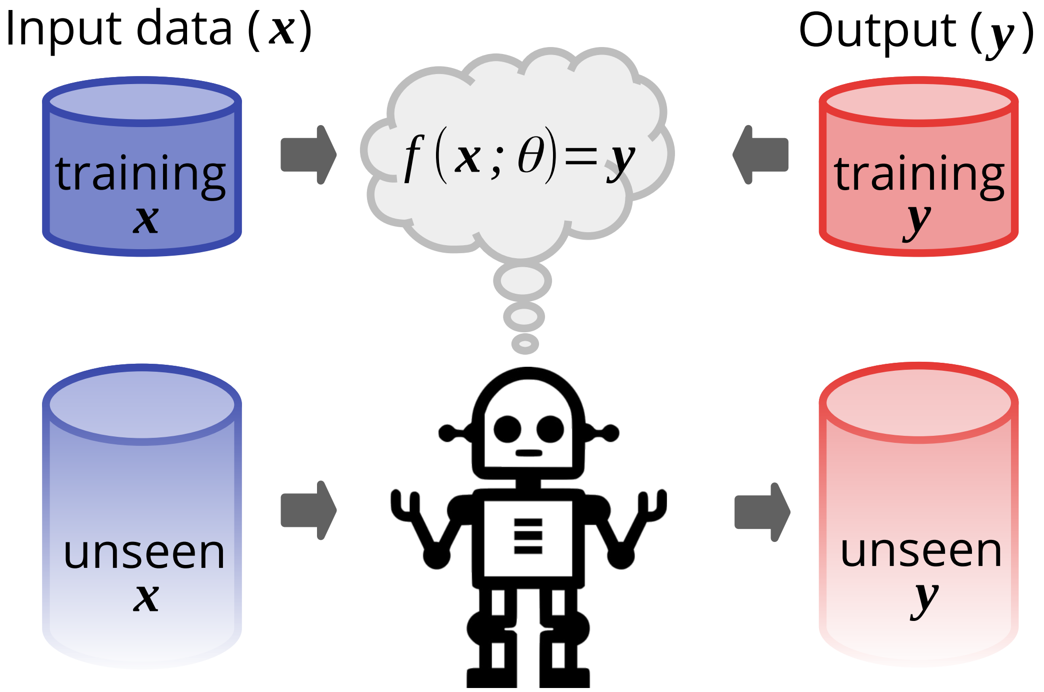
Neural network training pipeline

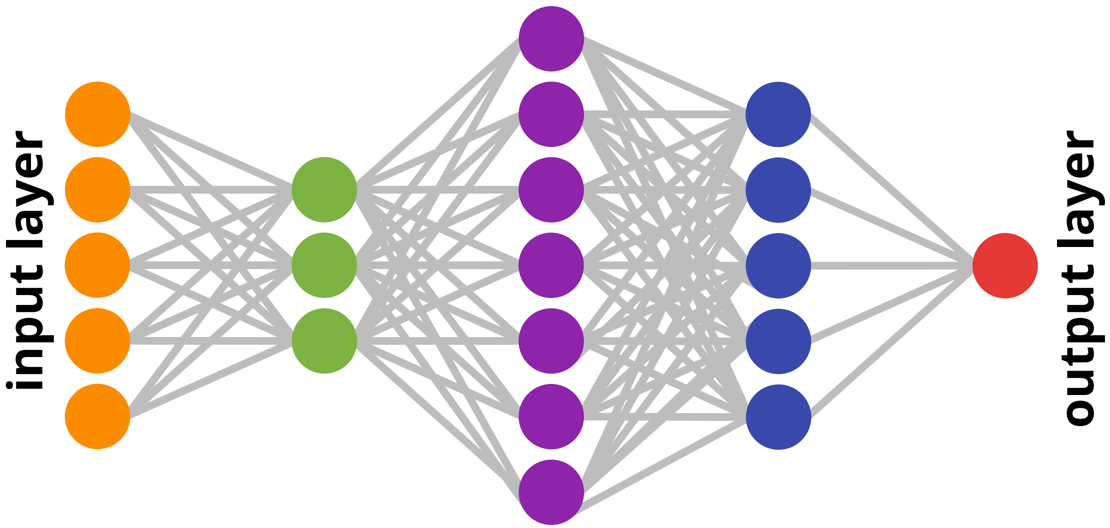
1 epoch

- Sample batch (input data x and target data y) from training dataset:
  - Evaluate model on batch input data (=prediction) in forward pass
  - Compute loss on prediction and target y
  - Compute weight gradients with backprop.
  - Modify weights based on gradients and learning rate
  - Repeat for all batches
- Repeat for a number of epochs, monitor training and validation loss + metrics
- Stop before overfitting sets in



Supervised learning with Neural Networks



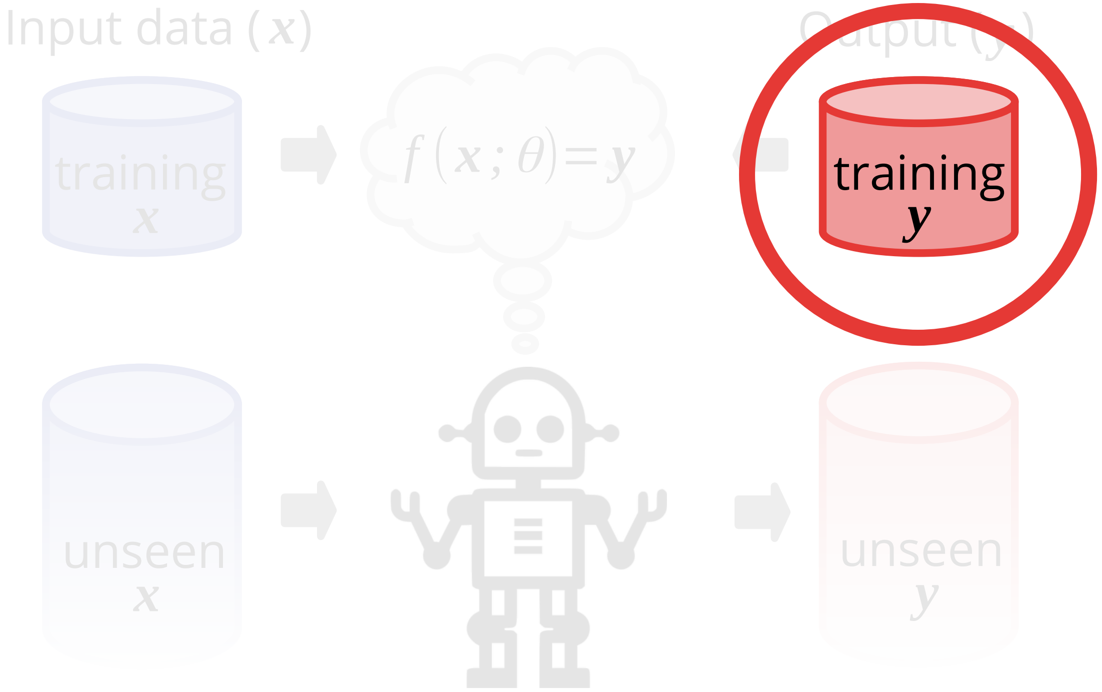


A machine learns a task from **annotated examples**.

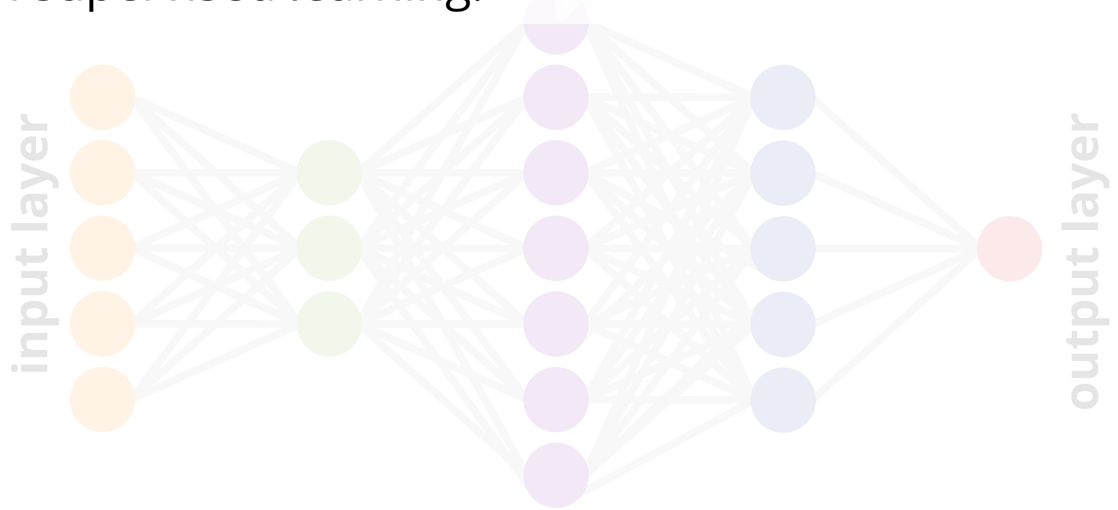
Mathematically, it learns a function, f, that maps input data, $\boldsymbol{x}$, to the output, $\boldsymbol{y}$.

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.

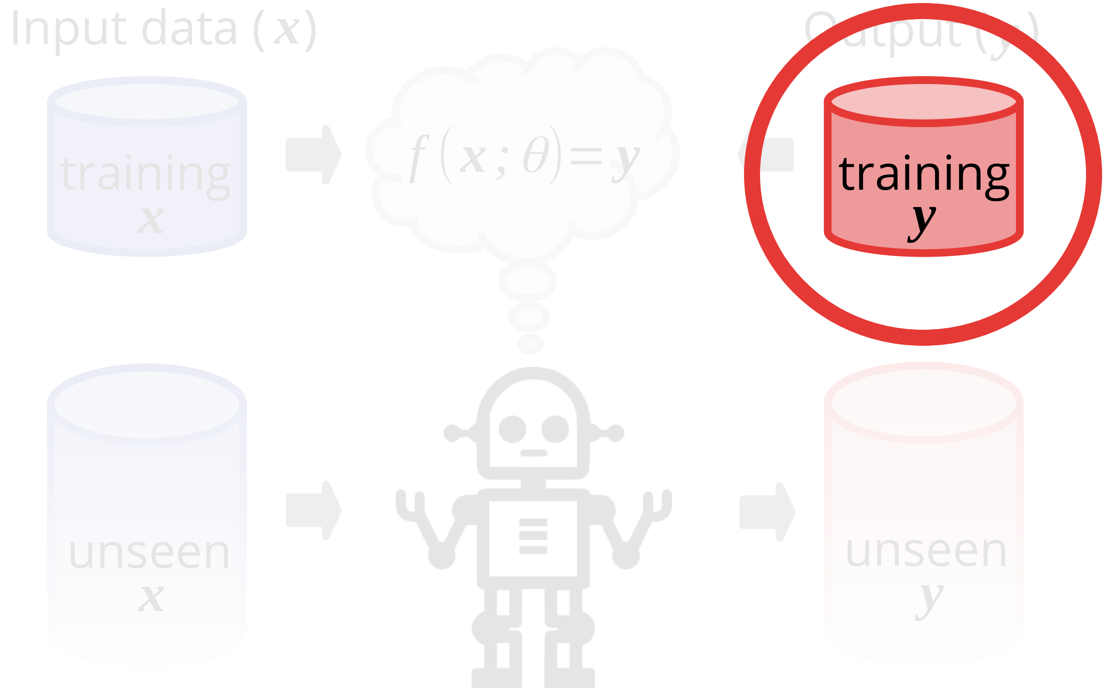


A machine learns a task from **annotated examples**.

Mathematically, it learns a function, f, that maps input data, x, to the output, y.

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.

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

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

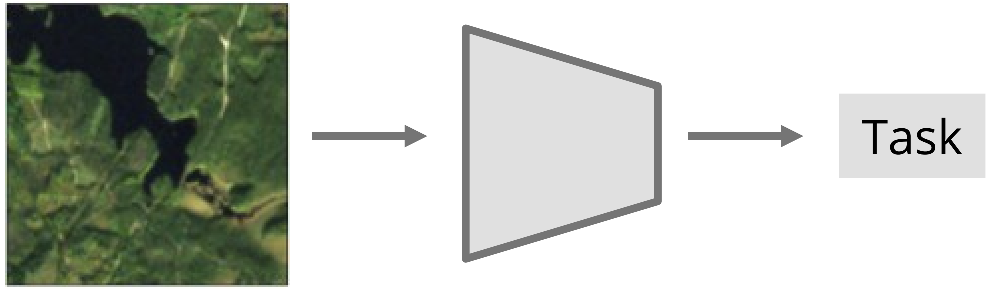
A machine learns a task from **annotated examples**.

Mathematically, it learns a function, f, that maps input data, x, to the output, y.

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

How can we use annotated data more efficiently?

- Data augmentations

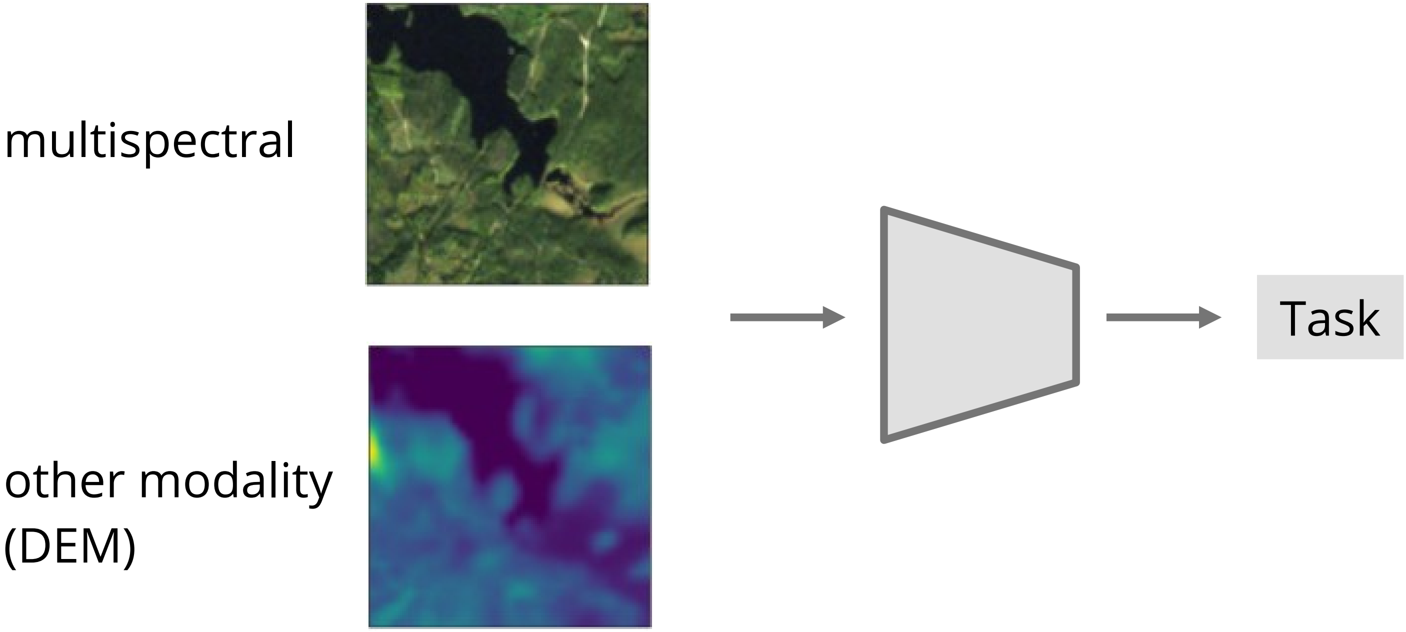


How can we use annotated data more efficiently?

- Data augmentations

How can we use annotated data more efficiently?

- Data augmentations
- Data Fusion



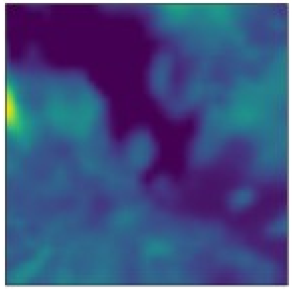
How can we use annotated data more efficiently?

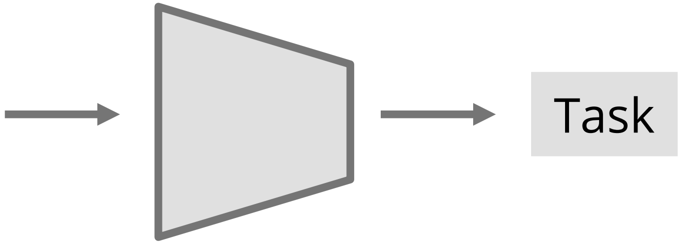
- Data augmentations
- Data Fusion

We will talk about this in the remainder of this session

multispectral

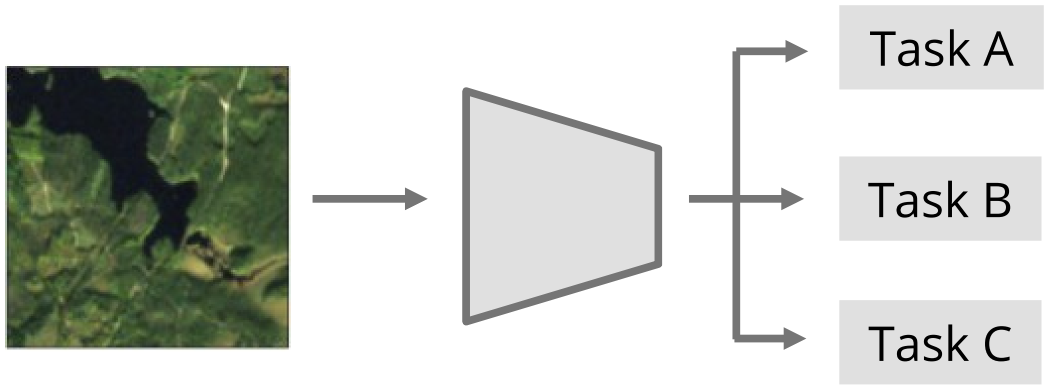
other modality (DEM)





How can we use annotated data more efficiently?

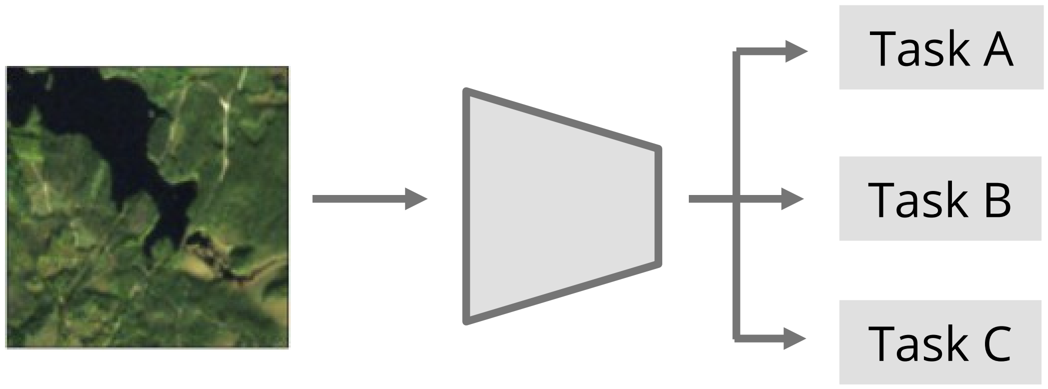
- Data augmentations
- Data Fusion
- Multi-task Learning



How can we use annotated data more efficiently?

- Data augmentations
- Data Fusion
- Multi-task Learning

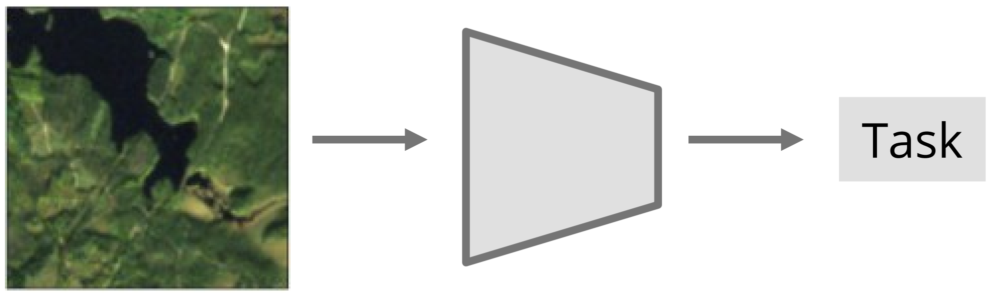
Joëlle will talk about this in the next session



How can we use annotated data more efficiently?

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

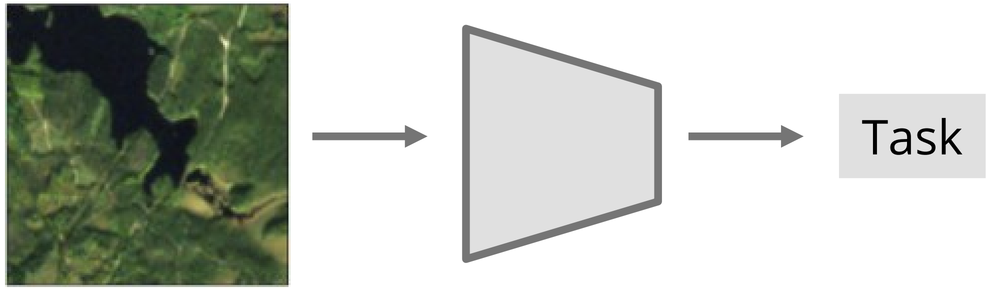
Can we pretrain a model from unannotated data?

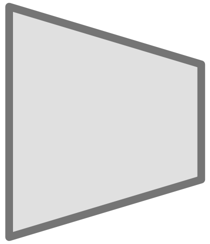


How can we use annotated data more efficiently?

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

Can we pretrain a model from unannotated data?

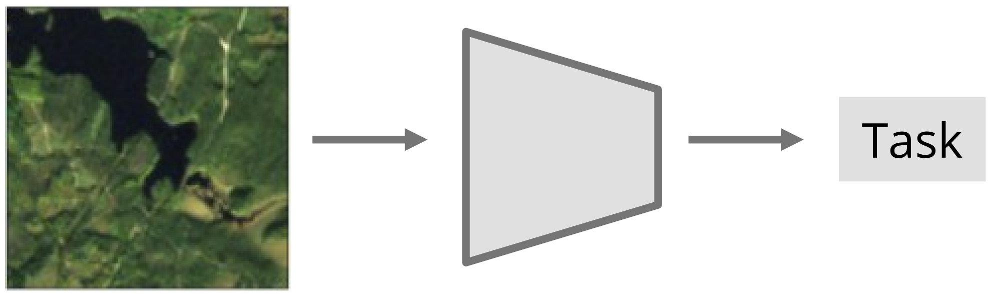




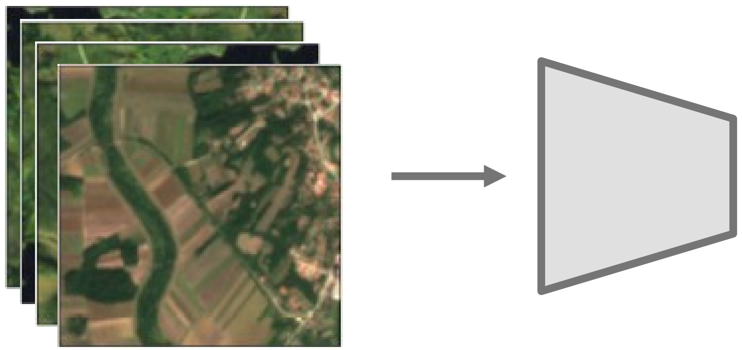
How can we use annotated data more efficiently?

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

Can we pretrain a model from unannotated data?



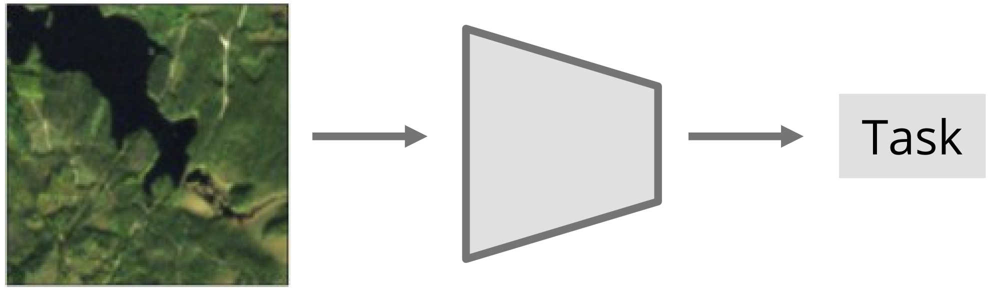
other dataset



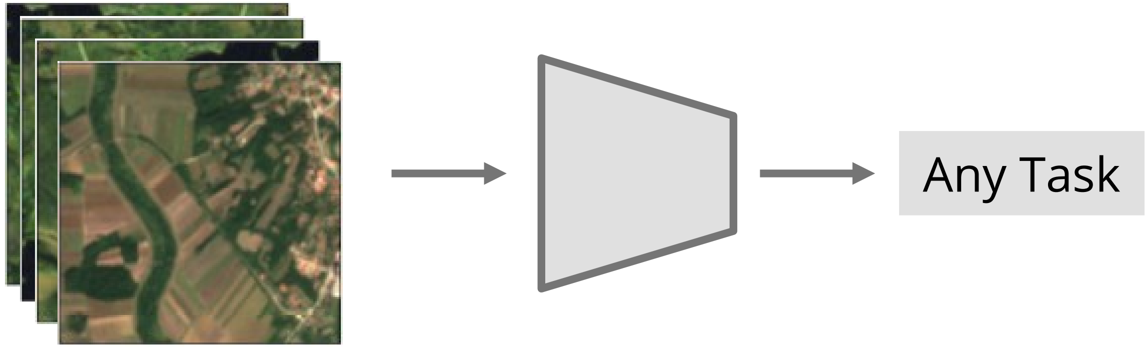
How can we use annotated data more efficiently?

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

Can we pretrain a model from unannotated data?



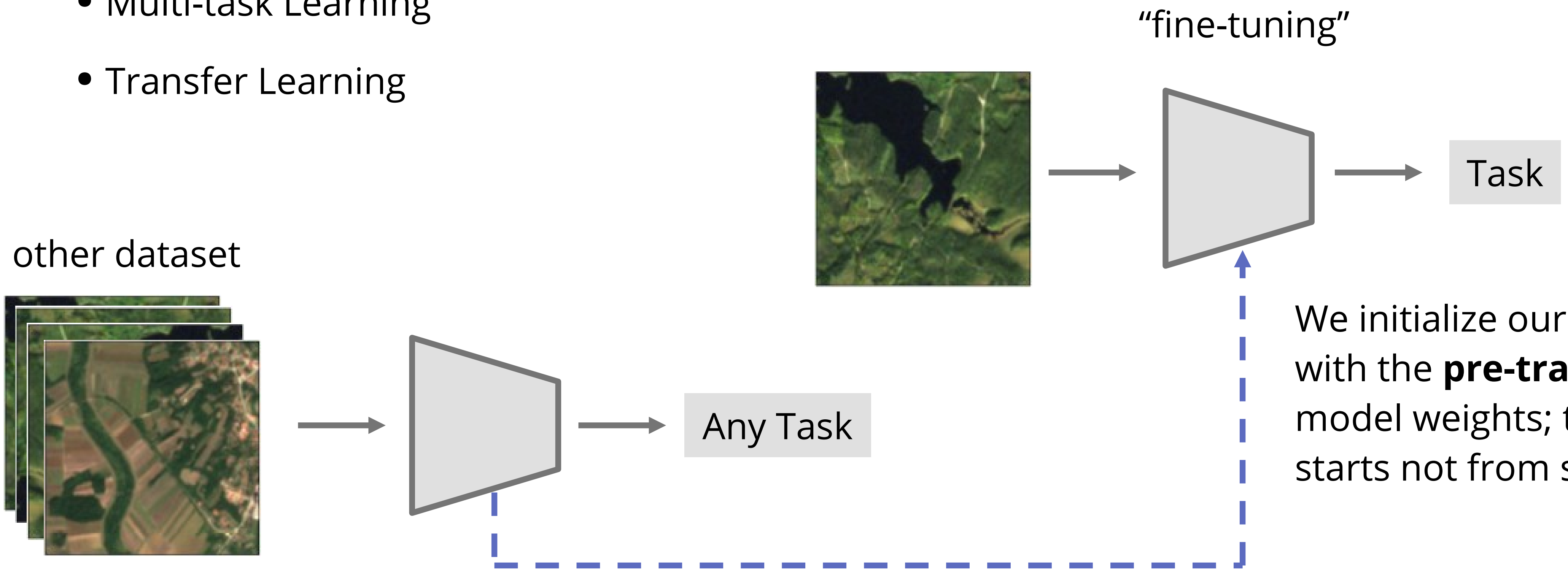
other dataset



How can we use annotated data more efficiently?

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

Can we pretrain a model from unannotated data?

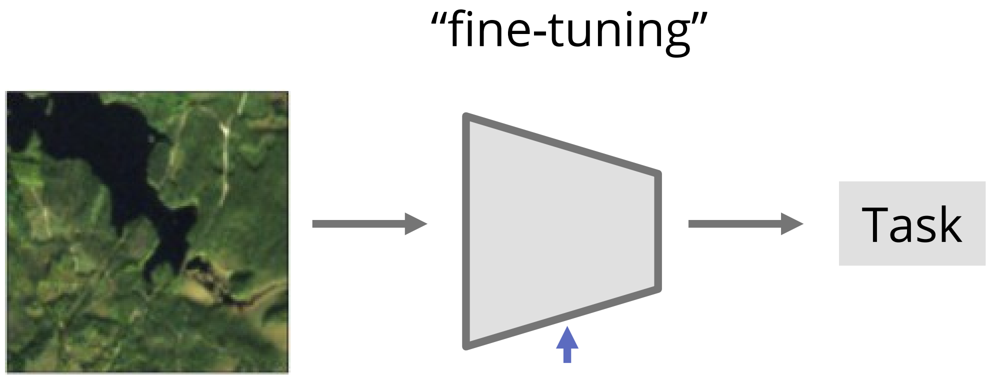


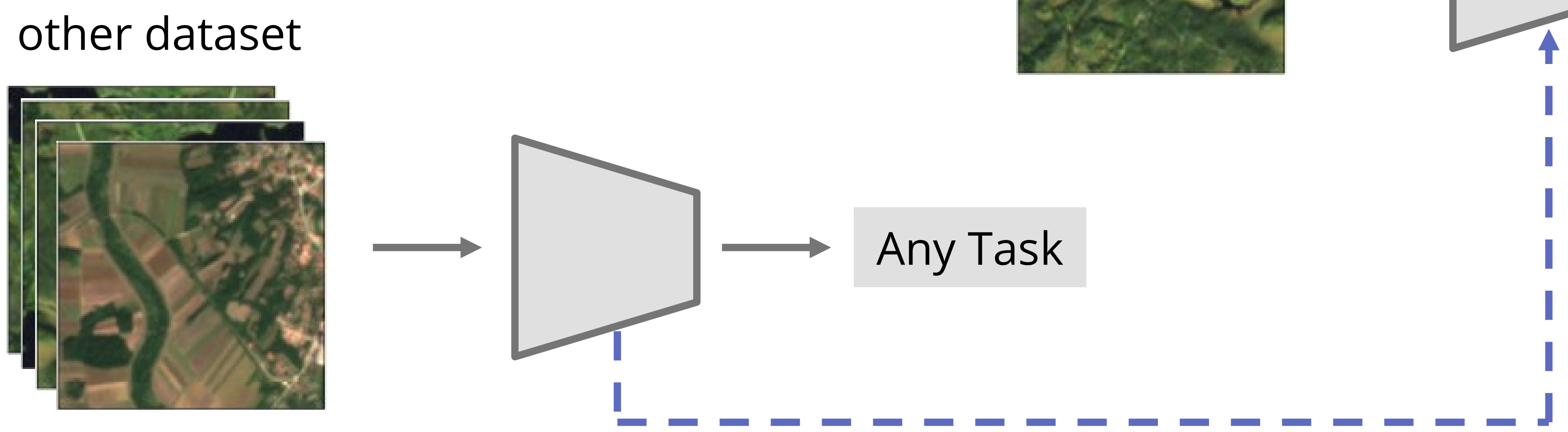
We initialize our model with the **pre-trained** model weights; training starts not from scratch!

How can we use annotated data more efficiently?

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

Can we pretrain a model from unannotated data?

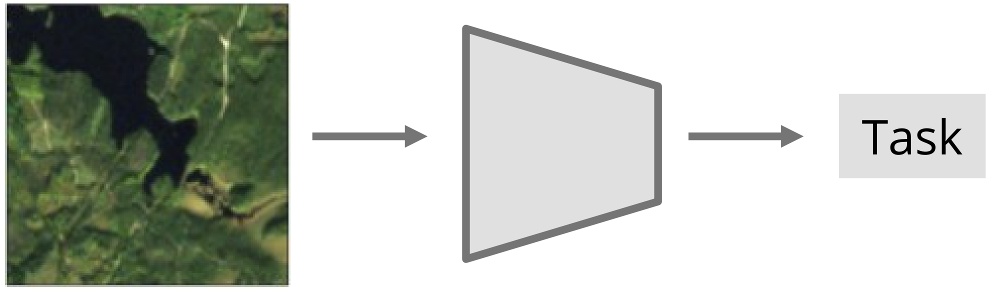




We initialize our model with the **pre-trained** model weights; training starts not from scratch!

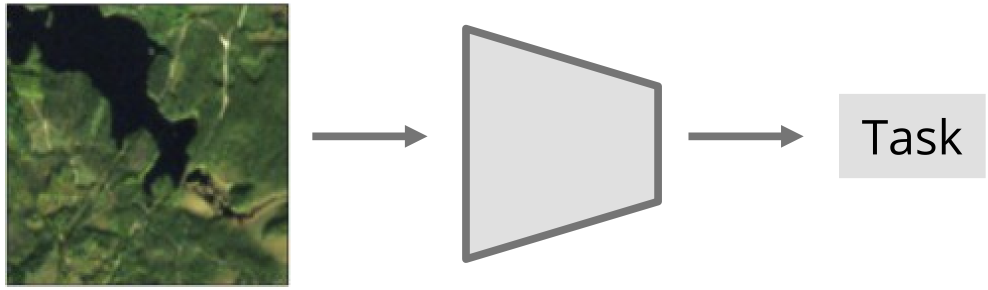
How can we use annotated data more efficiently?

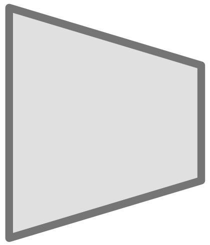
- Data augmentations
- Data Fusion
- Multi-task Learning
- Transfer Learning
- Self-supervised Learning



How can we use annotated data more efficiently?

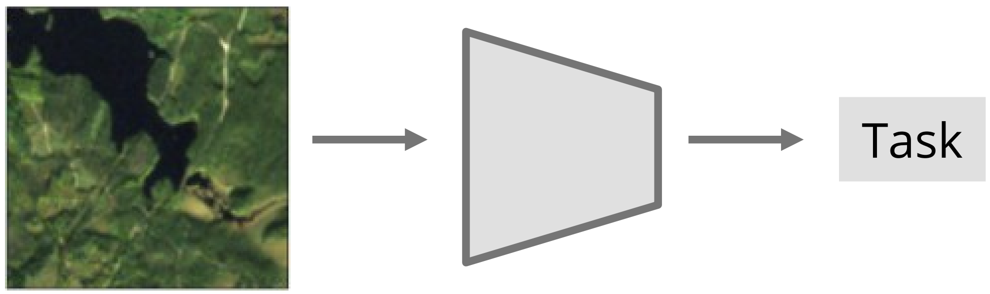
- Data augmentations
- Data Fusion
- Multi-task Learning
- Transfer Learning
- Self-supervised Learning



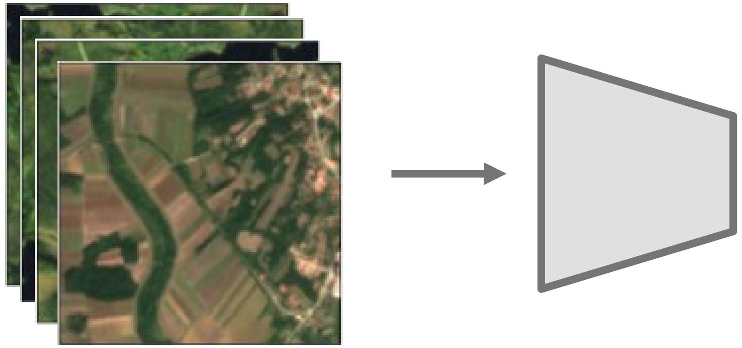


How can we use annotated data more efficiently?

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

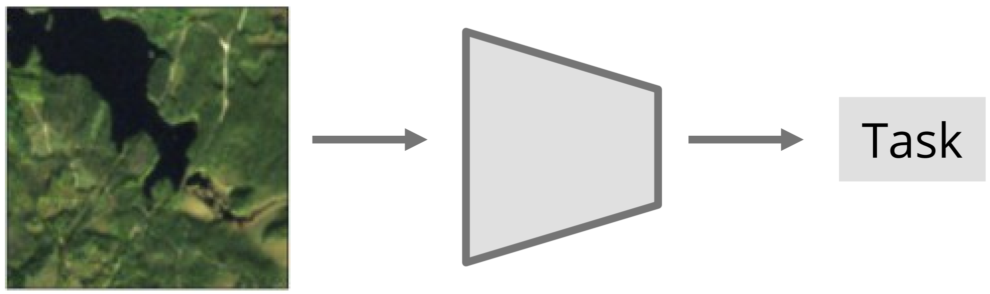


other dataset

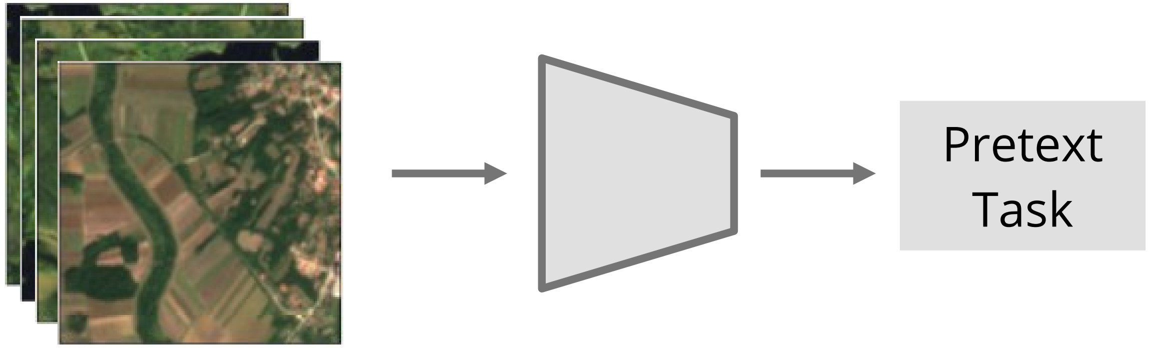


How can we use annotated data more efficiently?

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

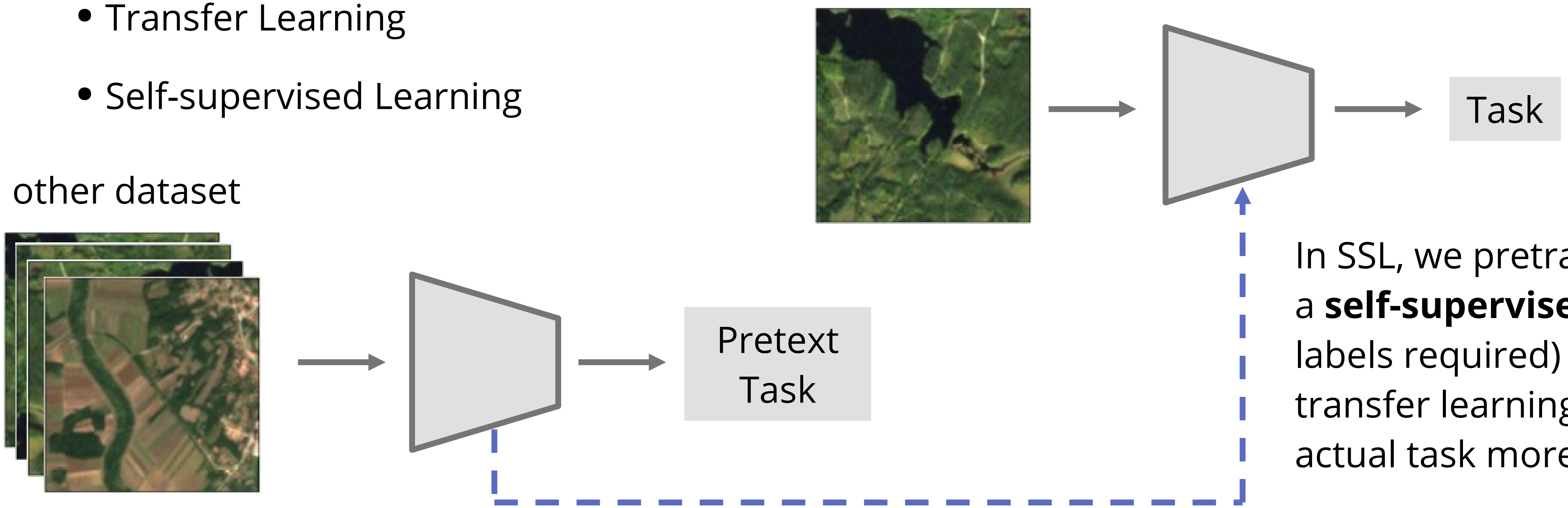


other dataset



How can we use annotated data more efficiently?

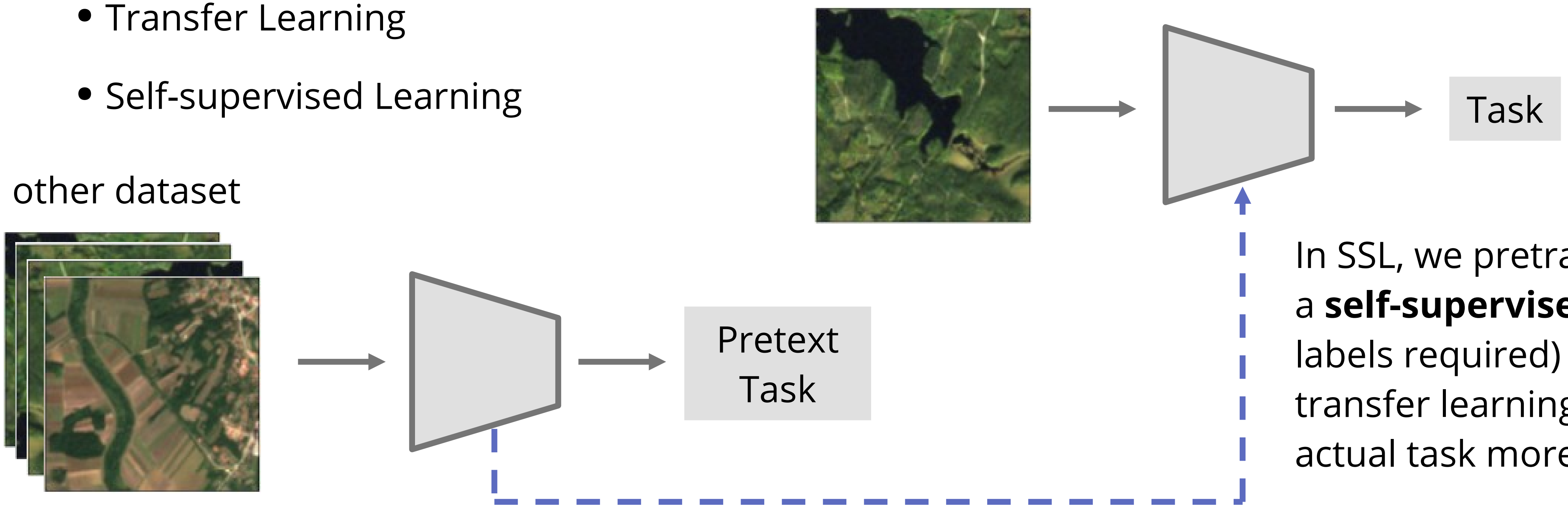
- Data augmentations
- Data Fusion
- Multi-task Learning
- Transfer Learning
- Self-supervised Learning



In SSL, we pretrain our model in a **self-supervised way** (no labels required) and then apply transfer learning to learn our actual task more efficiently.

How can we use annotated data more efficiently?

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



In SSL, we pretrain our model in a **self-supervised way** (no labels required) and then apply transfer learning to learn our actual task more efficiently.

How can we use annotated data more efficiently?

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

Damian and Linus will talk about this later

Task

other dataset

Pretext Task

In SSL, we pretrain our model in a **self-supervised way** (no labels required) and then apply transfer learning to learn our actual task more efficiently.

Data-efficient Deep Learning for Earth Observation

Data Fusion

Michael Mommert

Data Fusion

Data Fusion

Data Fusion is a technique in which different data modalities are combined (“fused”). The goal of data fusion is to better perform a task by combining relevant data.

Data Fusion

Data Fusion is a technique in which different data modalities are combined (“fused”). The goal of data fusion is to better perform a task by combining relevant data.

Earth observation is predestined for Data Fusion, as EO sensors collect data across many different data modalities:

Data Fusion

Data Fusion is a technique in which different data modalities are combined (“fused”). The goal of data fusion is to better perform a task by combining relevant data.

Earth observation is predestined for Data Fusion, as EO sensors collect data across many different data modalities:

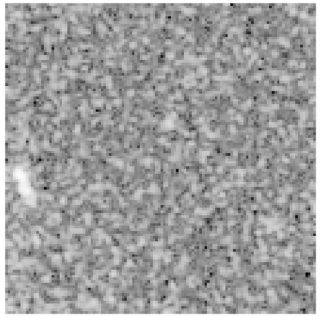
Multispectral
(e.g., Sentinel-2, Landsat)

Data Fusion

Data Fusion is a technique in which different data modalities are combined ("fused"). The goal of data fusion is to better perform a task by combining relevant data.

Earth observation is predestined for Data Fusion, as EO sensors collect data across many different data modalities:

Multispectral
(e.g., Sentinel-2, Landsat)



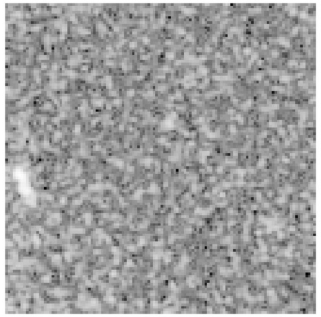
SAR
(e.g., Sentinel-1, ICEye)

Data Fusion

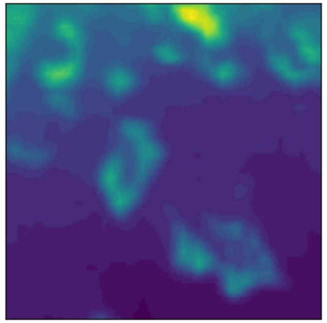
Data Fusion is a technique in which different data modalities are combined ("fused"). The goal of data fusion is to better perform a task by combining relevant data.

Earth observation is predestined for Data Fusion, as EO sensors collect data across many different data modalities:

Multispectral
(e.g., Sentinel-2, Landsat)



SAR
(e.g., Sentinel-1, ICEye)



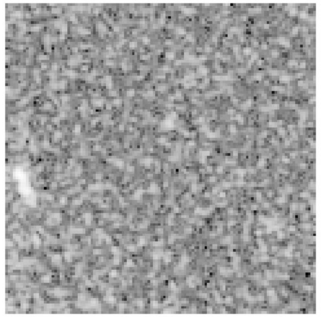
DEM
(e.g., Copernicus DEM)

Data Fusion

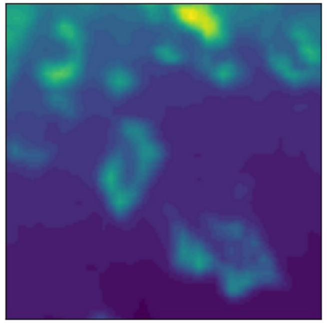
Data Fusion is a technique in which different data modalities are combined ("fused"). The goal of data fusion is to better perform a task by combining relevant data.

Earth observation is predestined for Data Fusion, as EO sensors collect data across many different data modalities:

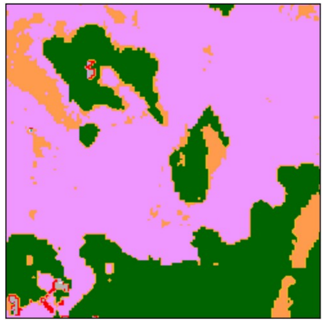
Multispectral
(e.g., Sentinel-2, Landsat)



SAR
(e.g., Sentinel-1, ICEye)



DEM
(e.g., Copernicus DEM)



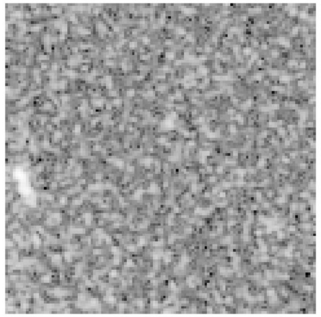
LU/LC
(e.g., Corine, Esa WorldCover)

Data Fusion

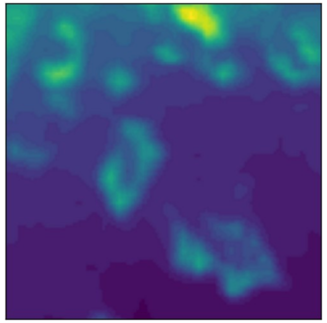
Data Fusion is a technique in which different data modalities are combined (“fused”). The goal of data fusion is to better perform a task by combining relevant data.

Earth observation is predestined for Data Fusion, as EO sensors collect data across many different data modalities:

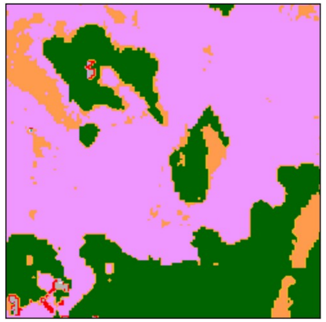
Multispectral
(e.g., Sentinel-2, Landsat)



SAR
(e.g., Sentinel-1, ICEye)



DEM
(e.g., Copernicus DEM)



LU/LC
(e.g., Corine, Esa WorldCover)

?

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

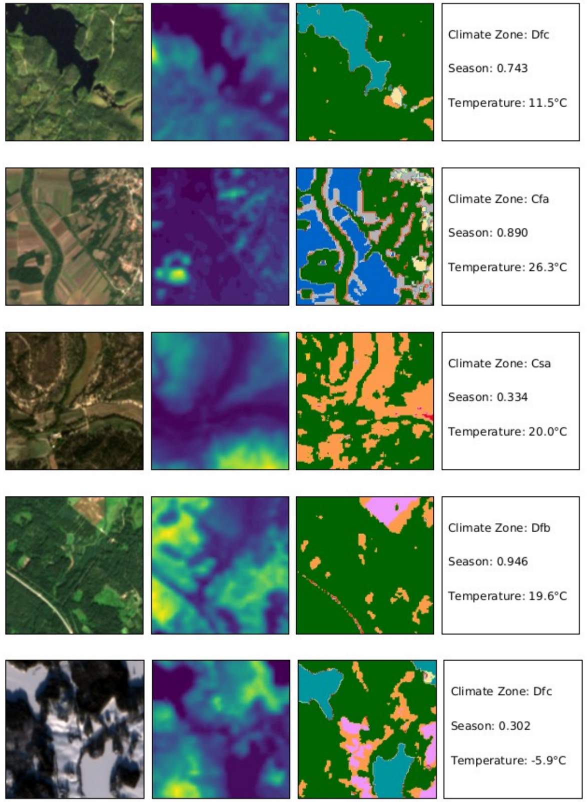
ben-ge: a truly multimodel dataset for EO

ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:

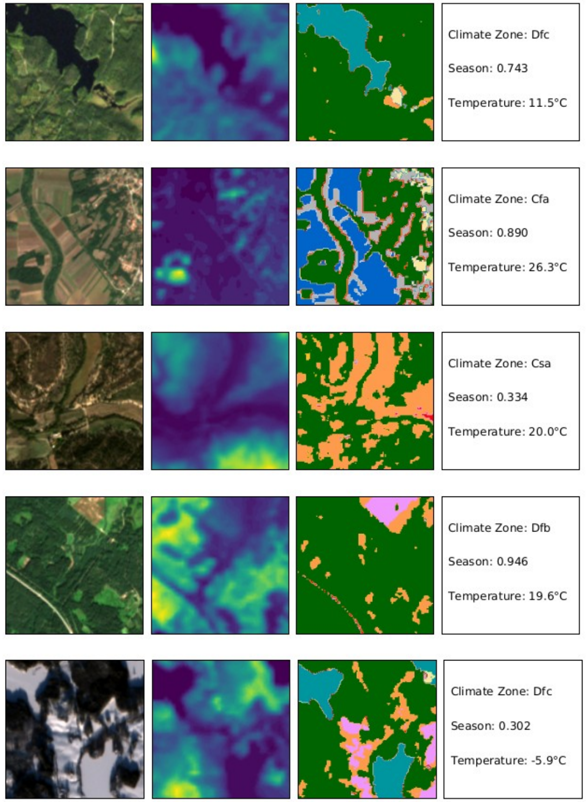
ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:



ben-ge: a truly multimodel dataset for EO

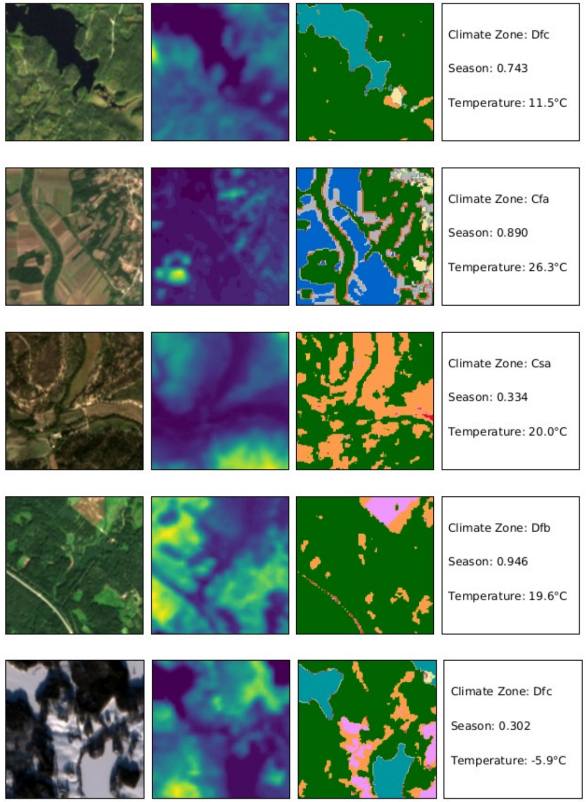
To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:



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

ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:

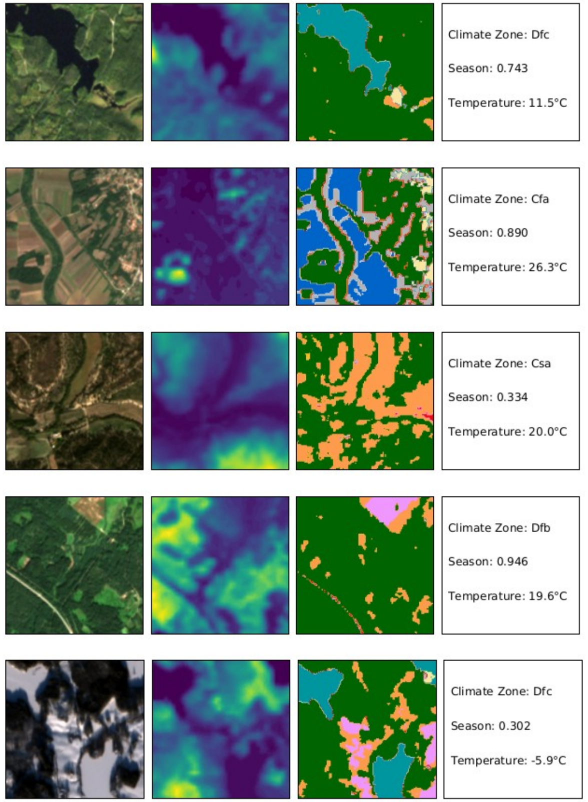


BigEarthNet contains 590,326 patches of co-located Sentinel-1/2 data.

ben-ge extends BigEarthNet by the following data modalities:

ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:



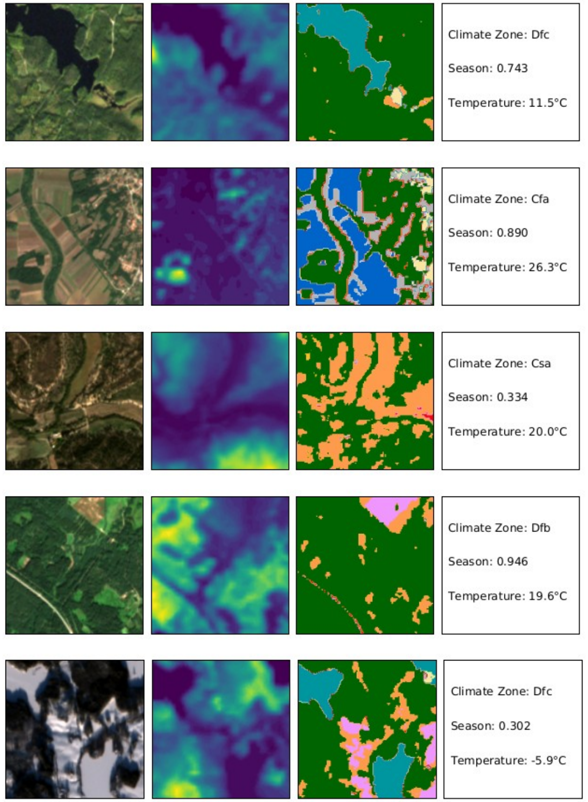
BigEarthNet contains 590,326 patches of co-located Sentinel-1/2 data.

ben-ge extends BigEarthNet by the following data modalities:

- Elevation data (Copernicus DEM GLO-30)

ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:



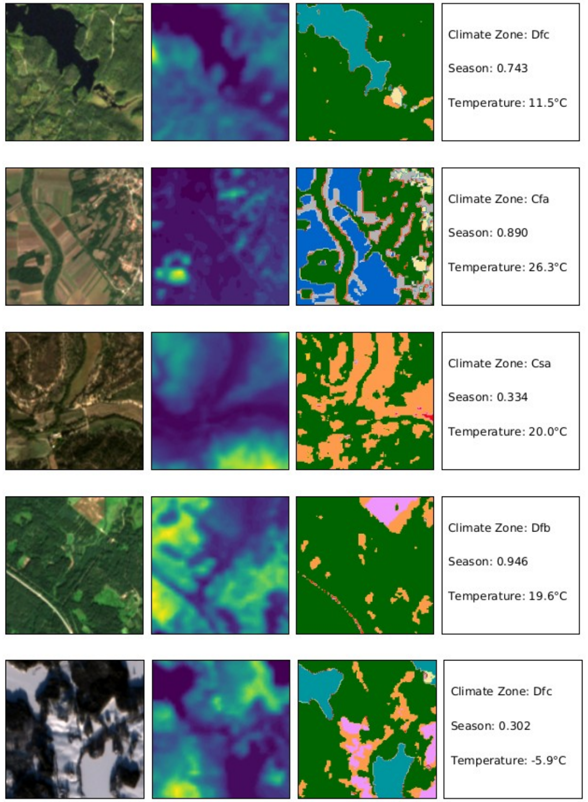
BigEarthNet contains 590,326 patches of co-located Sentinel-1/2 data.

ben-ge extends BigEarthNet by the following data modalities:

- Elevation data (Copernicus DEM GLO-30)
- Land-use/land-cover maps (ESA Worldcover)

ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:



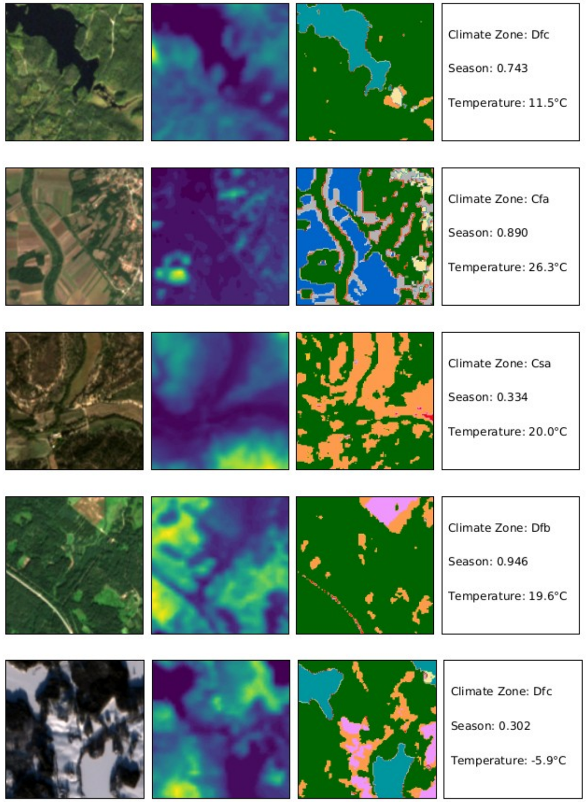
BigEarthNet contains 590,326 patches of co-located Sentinel-1/2 data.

ben-ge extends BigEarthNet by the following data modalities:

- Elevation data (Copernicus DEM GLO-30)
- Land-use/land-cover maps (ESA Worldcover)
- Environmental data (ERA-5)

ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:



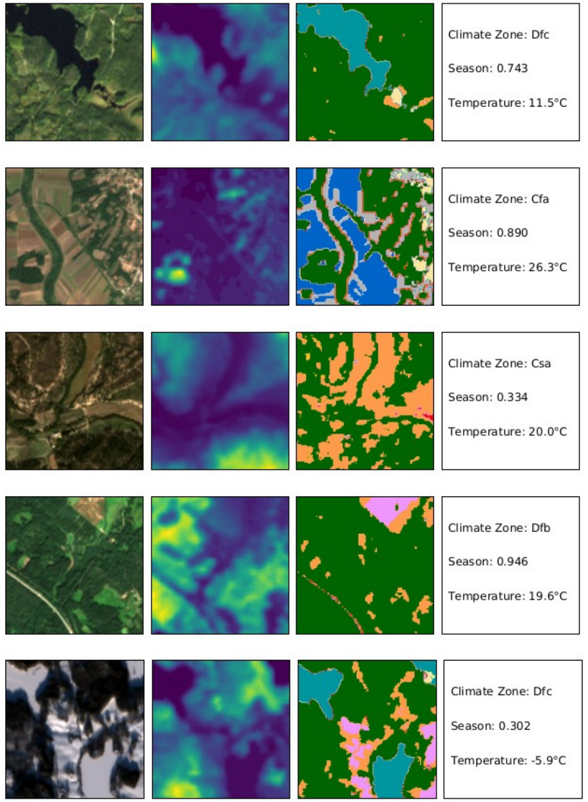
BigEarthNet contains 590,326 patches of co-located Sentinel-1/2 data.

ben-ge extends BigEarthNet by the following data modalities:

- Elevation data (Copernicus DEM GLO-30)
- Land-use/land-cover maps (ESA Worldcover)
- Environmental data (ERA-5)
- Climate zone classification (Beck et al. 2018)

ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:



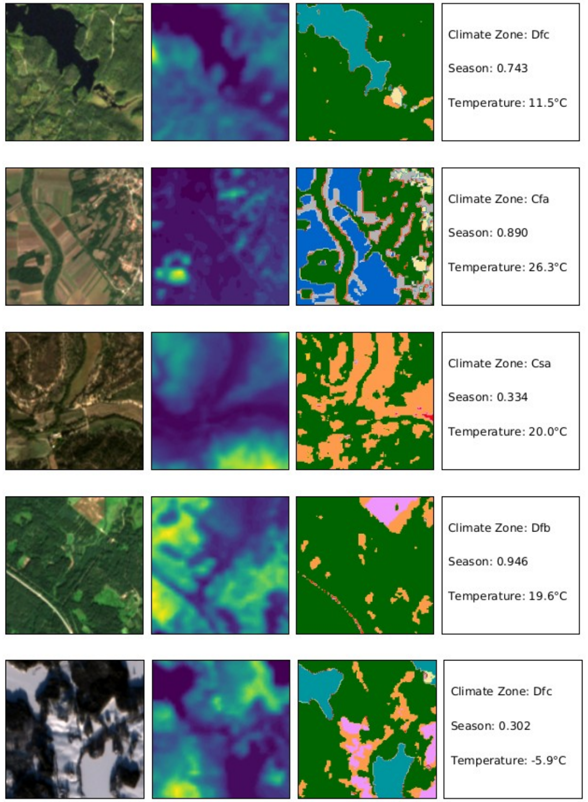
BigEarthNet contains 590,326 patches of co-located Sentinel-1/2 data.

ben-ge extends BigEarthNet by the following data modalities:

- Elevation data (Copernicus DEM GLO-30)
- Land-use/land-cover maps (ESA Worldcover)
- Environmental data (ERA-5)
- Climate zone classification (Beck et al. 2018)
- Seasonal encoding

ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:



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

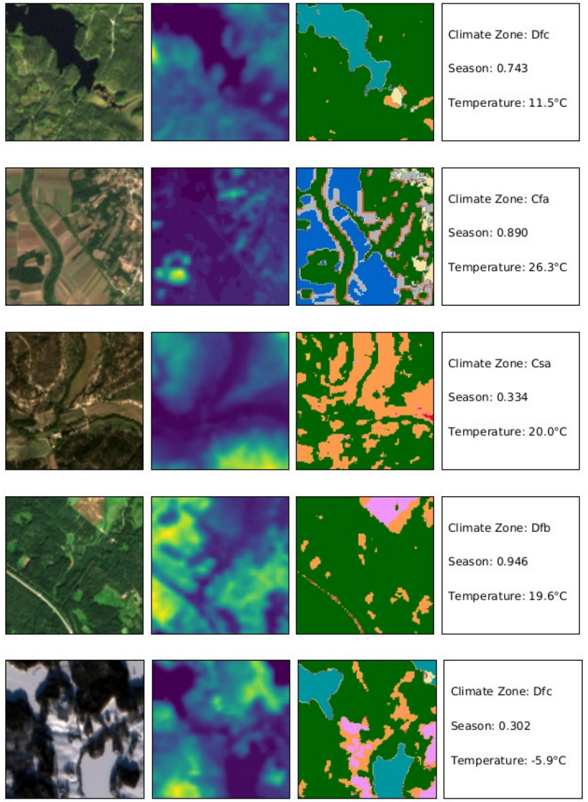
ben-ge extends BigEarthNet by the following data modalities:

- Elevation data (Copernicus DEM GLO-30)
- Land-use/land-cover maps (ESA Worldcover)
- Environmental data (ERA-5)
- Climate zone classification (Beck et al. 2018)
- Seasonal encoding

ben-ge serves as a testbed for combining different EO data modalities.

ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:



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

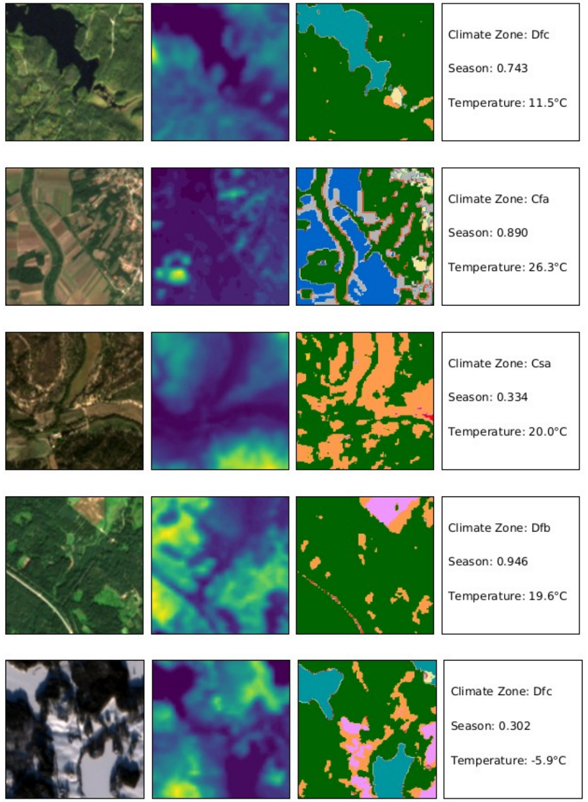
ben-ge extends BigEarthNet by the following data modalities:

- Elevation data (Copernicus DEM GLO-30)
- Land-use/land-cover maps (ESA Worldcover)
- Environmental data (ERA-5)
- Climate zone classification (Beck et al. 2018)
- Seasonal encoding

ben-ge serves as a testbed for combining different EO data modalities. For more details, check out https://github.com/HSG-AIML/ben-ge

ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:



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

ben-ge extends BigEarthNet by the following data modalities:

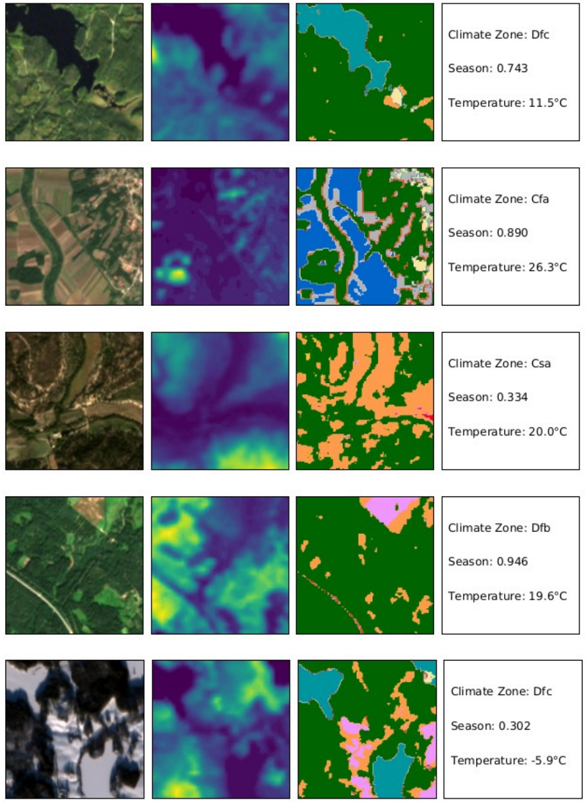
- Elevation data (Copernicus DEM GLO-30)
- Land-use/land-cover maps (ESA Worldcover)
- Environmental data (ERA-5)
- Climate zone classification (Beck et al. 2018)
- Seasonal encoding

ben-ge serves as a testbed for combining different EO data modalities. For more details, check out https://github.com/HSG-AIML/ben-ge

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

ben-ge: a truly multimodel dataset for EO

To explore the use of multimodal for Data Fusion (and other methods), we will use a specifically designed dataset:



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

ben-ge extends BigEarthNet by the following data modalities:

- Elevation data (Copernicus DEM GLO-30)
- Land-use/land-cover maps (ESA Worldcover)
- Environmental data (ERA-5)
- Climate zone classification (Beck et al. 2018)
- Seasonal encoding

Come and see our ben-ge presentation: WE2.R10.3, Wed, 10:39-10:51, Rm 101

ben-ge serves as a testbed for combining different EO data modalities. For more details, check out https://github.com/HSG-AIML/ben-ge

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

ben-ge: a truly multimodel dataset for EO

What data modalities are available in ben-ge?

ben-ge: a truly multimodel dataset for EO

What data modalities are available in ben-ge?

Sentinel-2
Multispectral

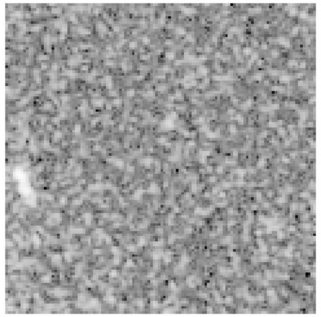
12 bands
Level-2A

ben-ge: a truly multimodel dataset for EO

What data modalities are available in ben-ge?

Sentinel-2
Multispectral

12 bands
Level-2A



Sentinel-1
SAR

2 bands

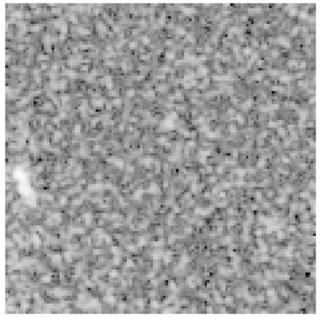
ben-ge: a truly multimodel dataset for EO

What data modalities are available in ben-ge?

BigEarthNet-MM

Sentinel-2
Multispectral

12 bands
Level-2A



Sentinel-1
SAR

2 bands

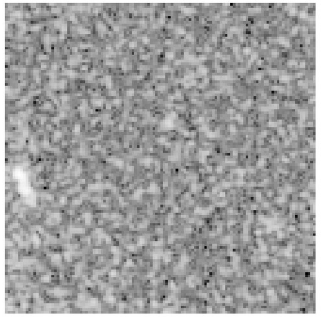
ben-ge: a truly multimodel dataset for EO

What data modalities are available in ben-ge?

BigEarthNet-MM

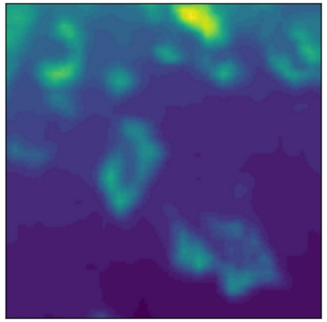
Sentinel-2
Multispectral

12 bands
Level-2A



Sentinel-1
SAR

2 bands



Copernicus
DEM
(GLO-30,
resampled)

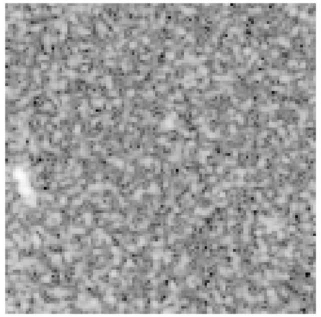
ben-ge: a truly multimodel dataset for EO

What data modalities are available in ben-ge?

BigEarthNet-MM

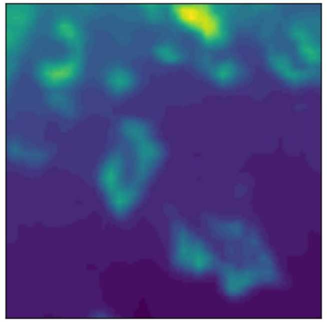
Sentinel-2
Multispectral

12 bands
Level-2A

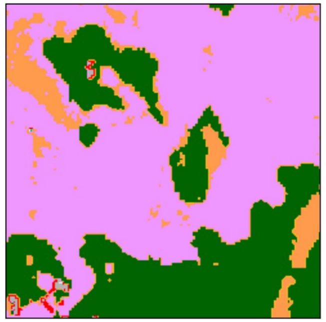


Sentinel-1
SAR

2 bands



Copernicus
DEM
(GLO-30,
resampled)



ESA WorldCover
LU/LC

8/11 classes

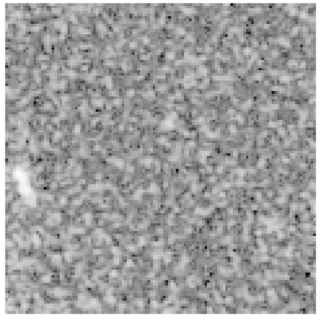
ben-ge: a truly multimodel dataset for EO

What data modalities are available in ben-ge?

BigEarthNet-MM

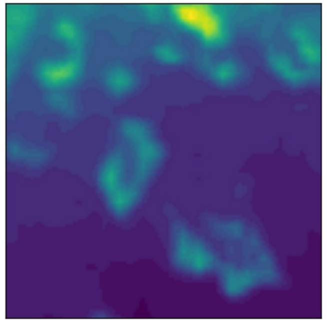
Sentinel-2
Multispectral

12 bands
Level-2A

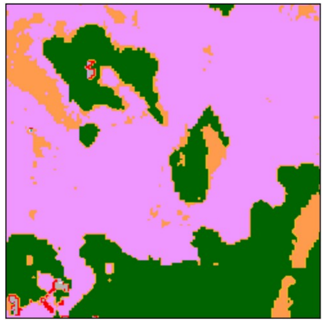


Sentinel-1
SAR

2 bands



Copernicus
DEM
(GLO-30,
resampled)



ESA WorldCover
LU/LC

8/11 classes

?

Meta Data

ERA-5 weather
Climate zones
Seasonality

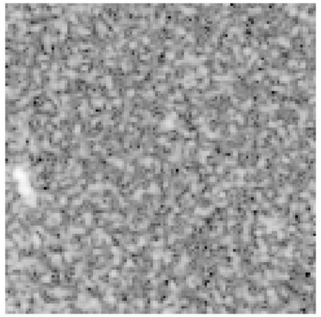
ben-ge: a truly multimodel dataset for EO

What data modalities are available in ben-ge?

BigEarthNet-MM

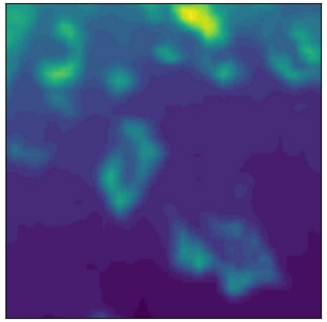
Sentinel-2
Multispectral

12 bands
Level-2A

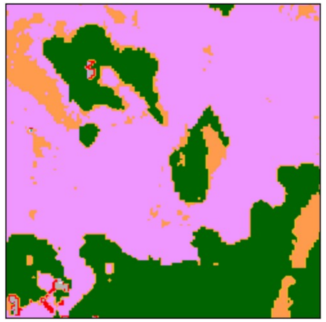


Sentinel-1
SAR

2 bands



Copernicus
DEM
(GLO-30,
resampled)



ESA WorldCover
LU/LC

8/11 classes

?

Meta Data

ERA-5 weather
Climate zones
Seasonality

10m resolution

Data Fusion for Deep Learning

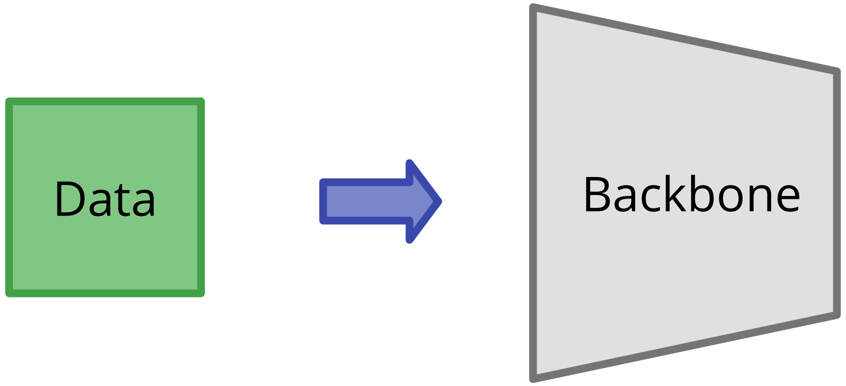
How can we leverage Data Fusion in Deep Learning?

Early Fusion

Data

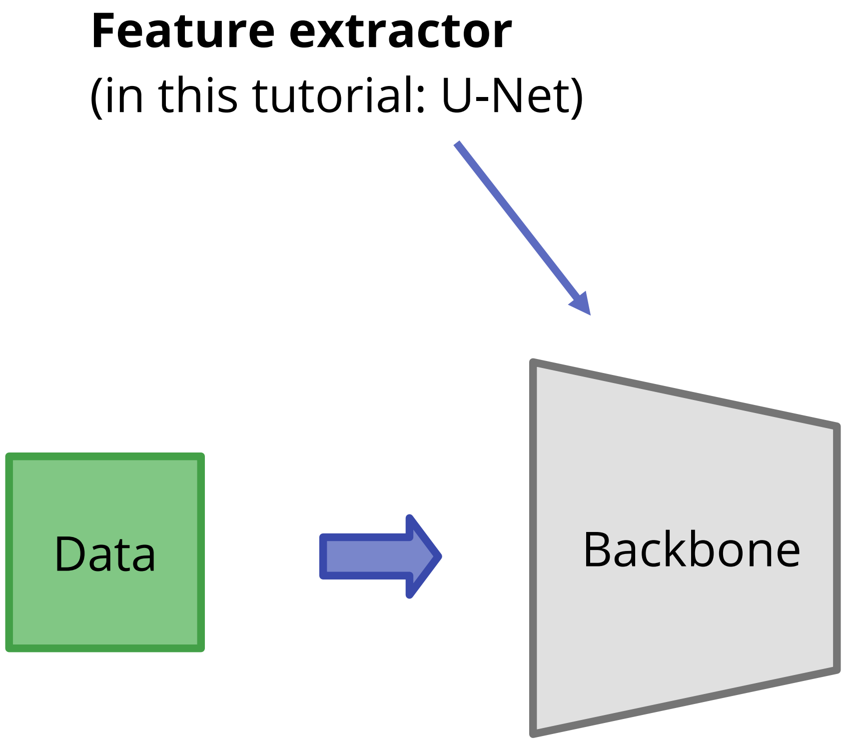
"Default supervised learning setup"

Early Fusion



"Default supervised learning setup"

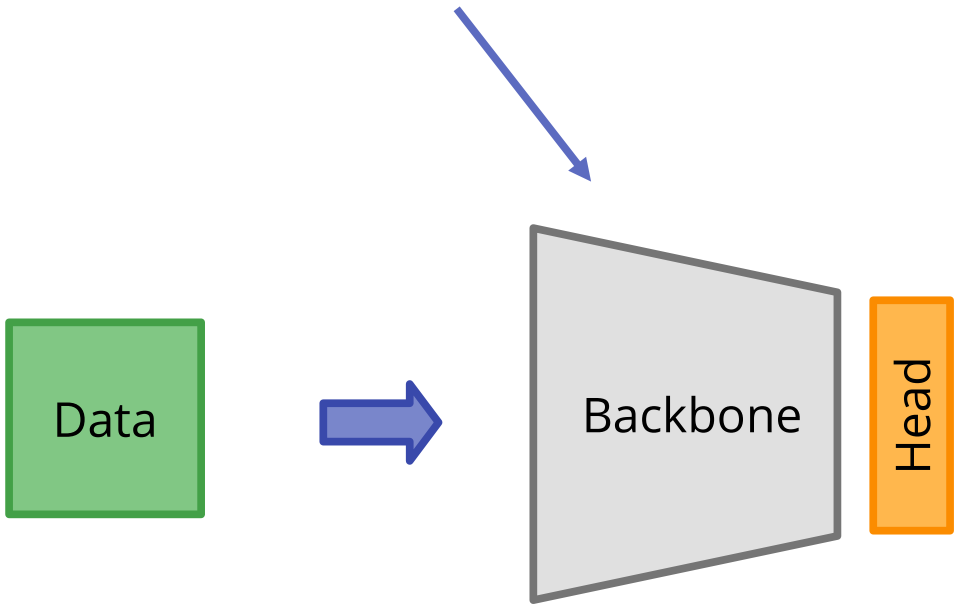
Early Fusion



"Default supervised learning setup"

Early Fusion

Feature extractor
(in this tutorial: U-Net)

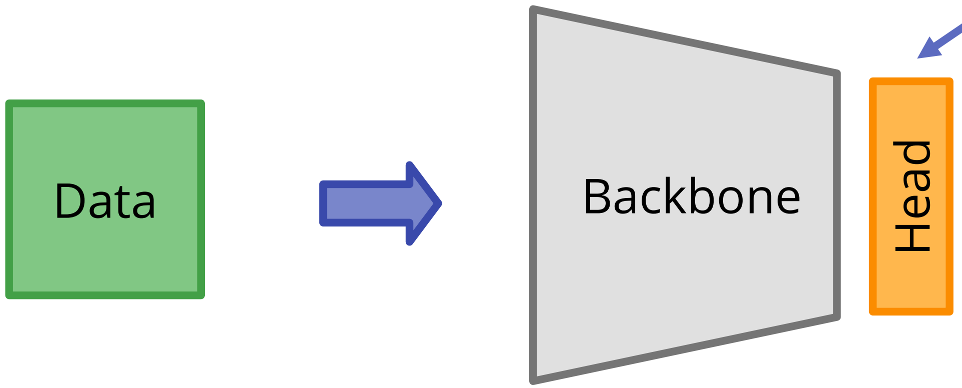


“Default supervised learning setup”

Early Fusion

Feature extractor
(in this tutorial: U-Net)

“Head” predicts the target based on the learned representations (features); e.g., classification head.

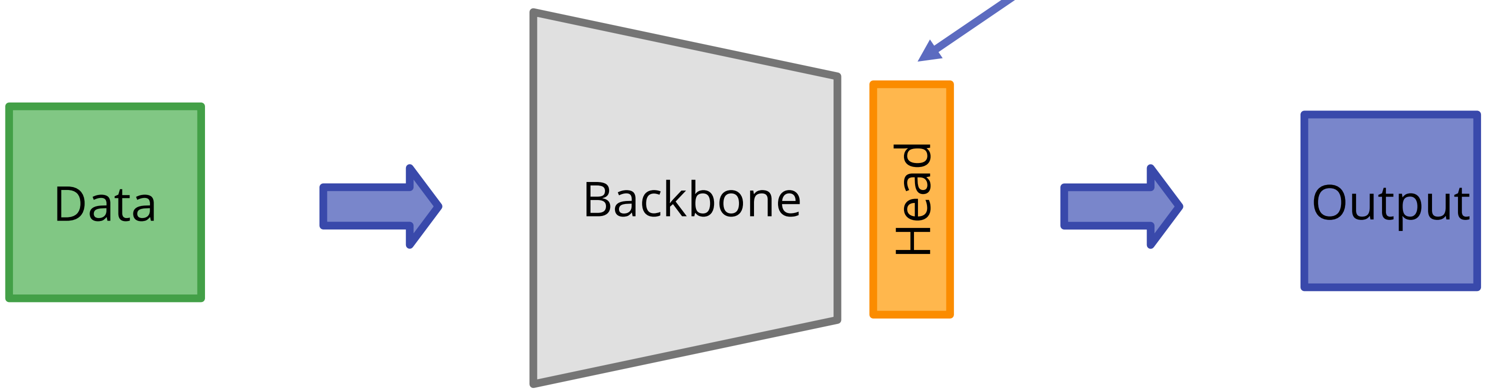


“Default supervised learning setup”

Early Fusion

Feature extractor
(in this tutorial: U-Net)

"Head" predicts the target based on the learned representations (features); e.g., classification head.



"Default supervised learning setup"

Early Fusion

In Early Fusion, two (or more) data modalities are combined before they enter the backbone:

Early Fusion

In Early Fusion, two (or more) data modalities are combined before they enter the backbone:

Early Fusion

In Early Fusion, two (or more) data modalities are combined before they enter the backbone:

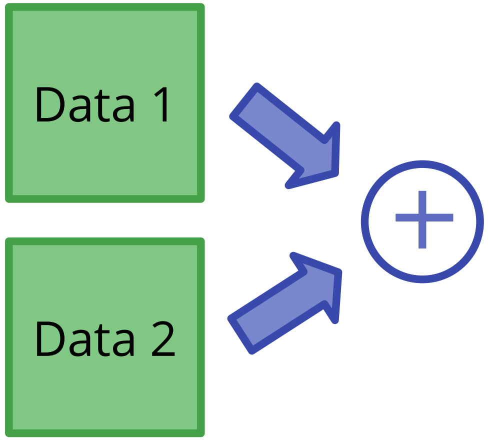
Data 1

Data 2

Different
data modalities

Early Fusion

In Early Fusion, two (or more) data modalities are combined before they enter the backbone:

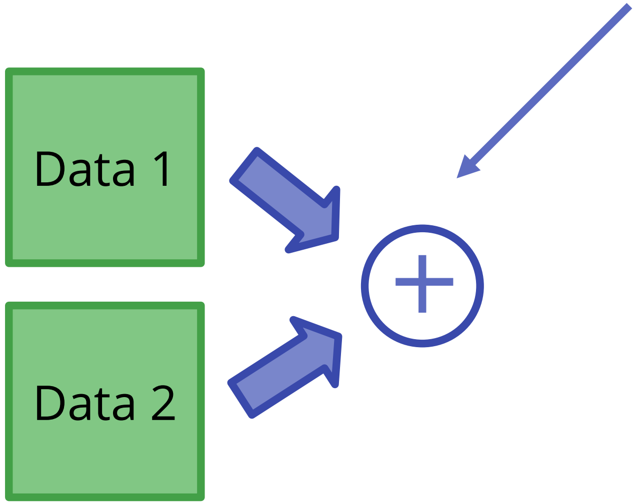


Different
data modalities

Early Fusion

In Early Fusion, two (or more) data modalities are combined before they enter the backbone:

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

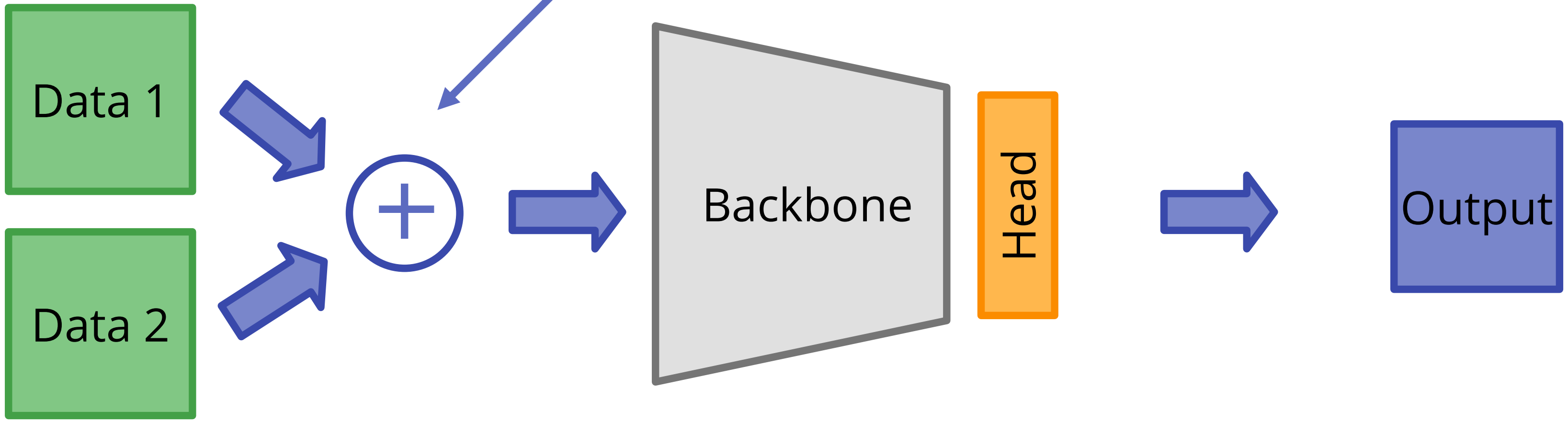


Different
data modalities

Early Fusion

In Early Fusion, two (or more) data modalities are combined before they enter the backbone:

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



Different
data modalities

Early Fusion: Different Data Shapes

Early Fusion: Different Data Shapes

Early Fusion is simple if the data modalities to be combined have the same shape (e.g., map-like features with the same extent).

Early Fusion: Different Data Shapes

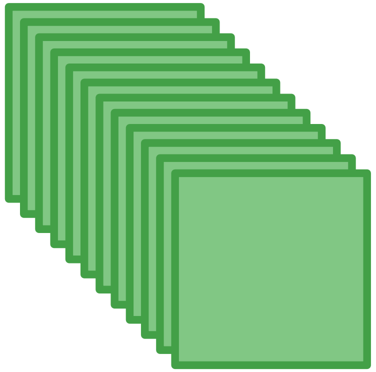
Early Fusion is simple if the data modalities to be combined have the same shape (e.g., map-like features with the same extent).

But: how to combine Sentinel-2 data (12 channels x 120 px x 120 px) with patch-global seasonality (scalar value in the range [0, 1]) data?

Early Fusion: Different Data Shapes

Early Fusion is simple if the data modalities to be combined have the same shape (e.g., map-like features with the same extent).

But: how to combine Sentinel-2 data (12 channels x 120 px x 120 px) with patch-global seasonality (scalar value in the range [0, 1]) data?

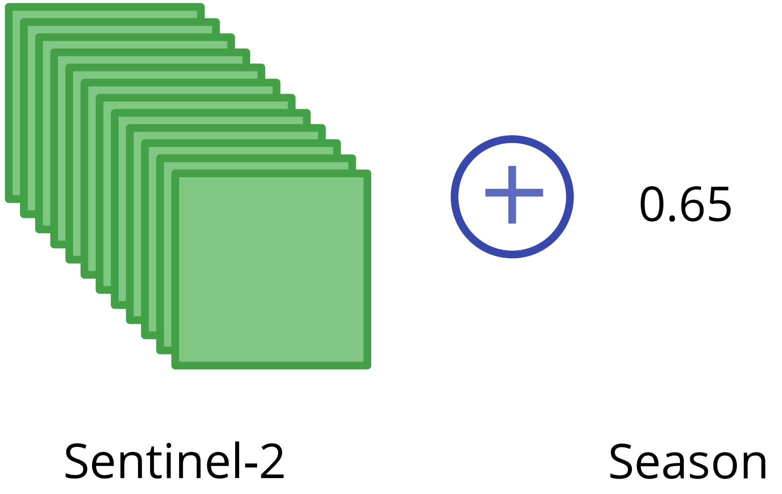


Sentinel-2

Early Fusion: Different Data Shapes

Early Fusion is simple if the data modalities to be combined have the same shape (e.g., map-like features with the same extent).

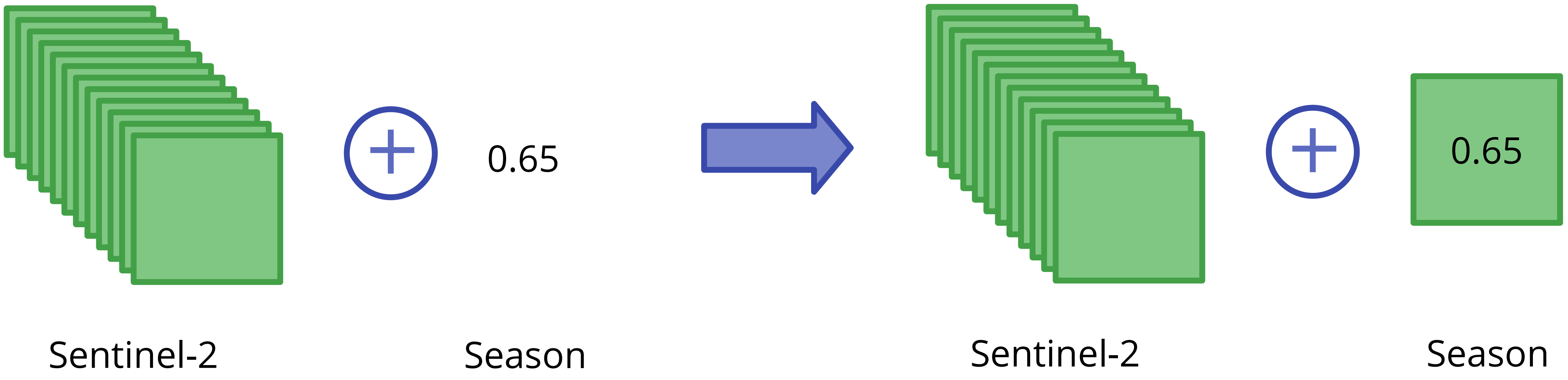
But: how to combine Sentinel-2 data (12 channels x 120 px x 120 px) with patch-global seasonality (scalar value in the range [0, 1]) data?



Early Fusion: Different Data Shapes

Early Fusion is simple if the data modalities to be combined have the same shape (e.g., map-like features with the same extent).

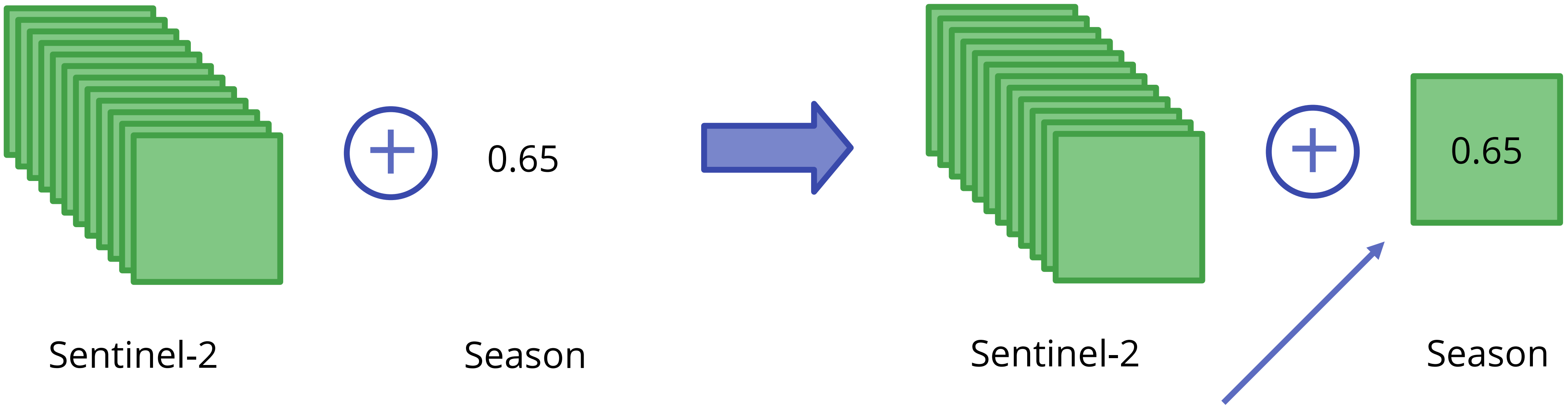
But: how to combine Sentinel-2 data (12 channels x 120 px x 120 px) with patch-global seasonality (scalar value in the range [0, 1]) data?



Early Fusion: Different Data Shapes

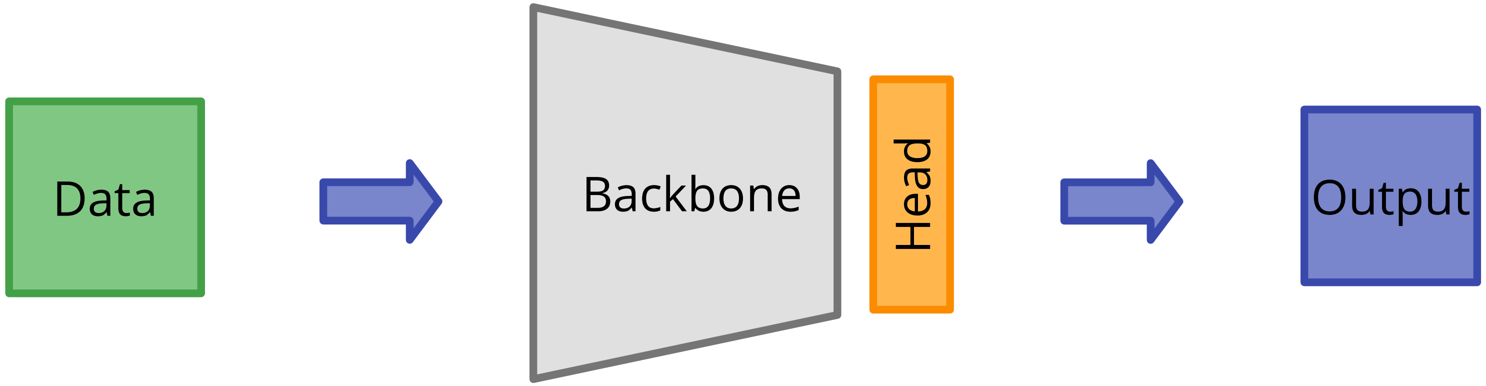
Early Fusion is simple if the data modalities to be combined have the same shape (e.g., map-like features with the same extent).

But: how to combine Sentinel-2 data (12 channels x 120 px x 120 px) with patch-global seasonality (scalar value in the range [0, 1]) data?



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

Late Fusion



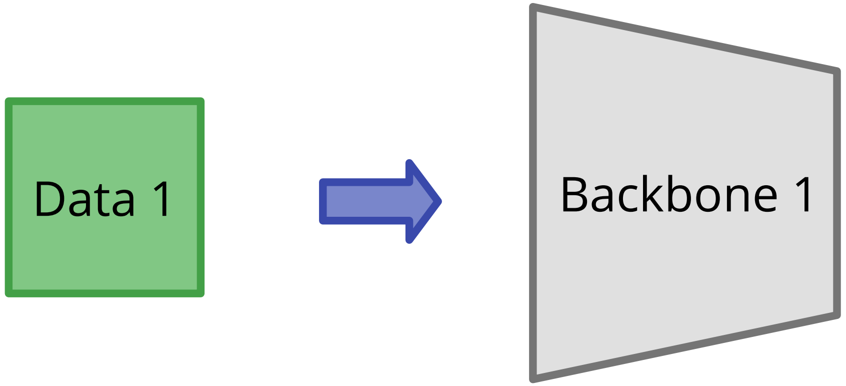
“Default supervised learning setup”

Late Fusion

In Late Fusion, two (or more) data modalities are combined after passing through separate backbones:

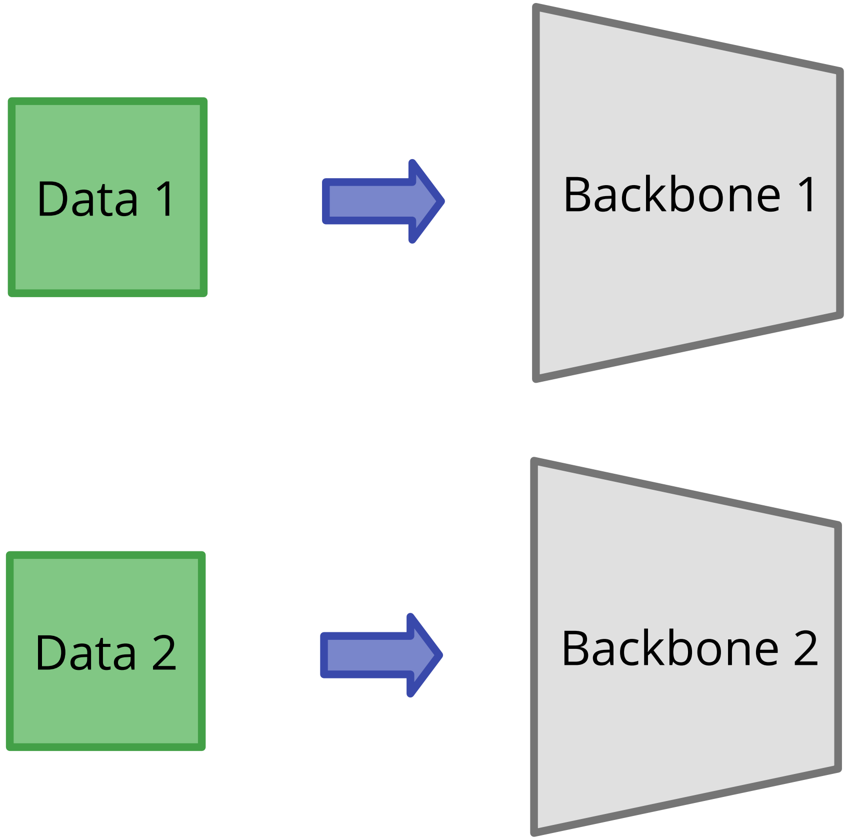
Late Fusion

In Late Fusion, two (or more) data modalities are combined after passing through separate backbones:



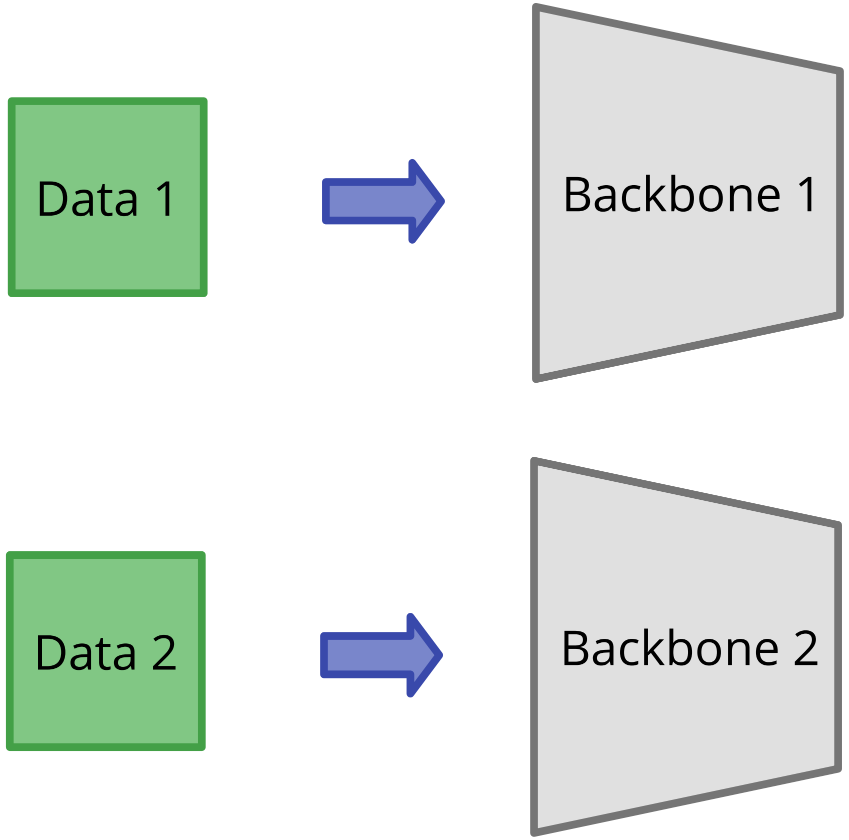
Late Fusion

In Late Fusion, two (or more) data modalities are combined after passing through separate backbones:



Late Fusion

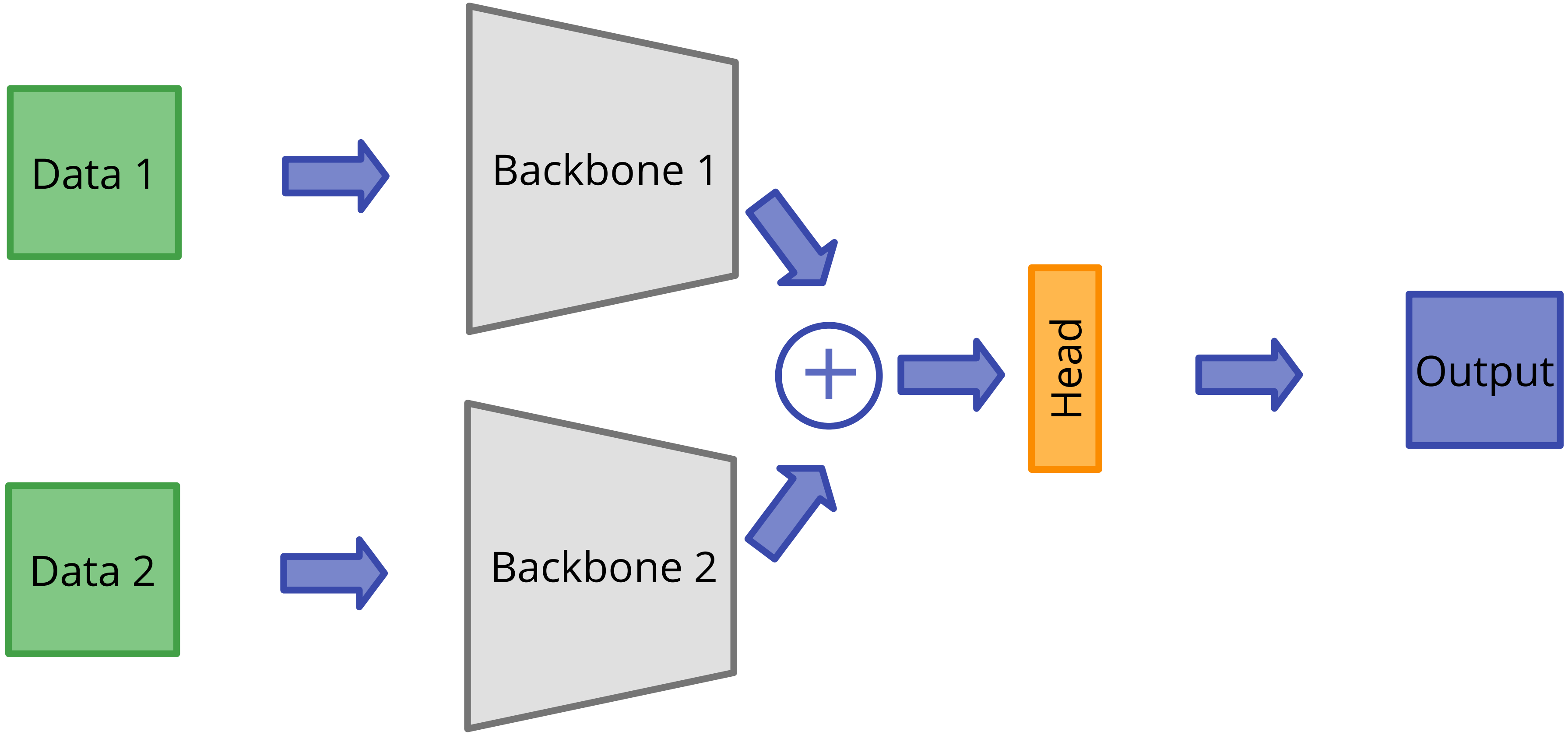
In Late Fusion, two (or more) data modalities are combined after passing through separate backbones:



Backbones might be completely separate, or have shared weights.

Late Fusion

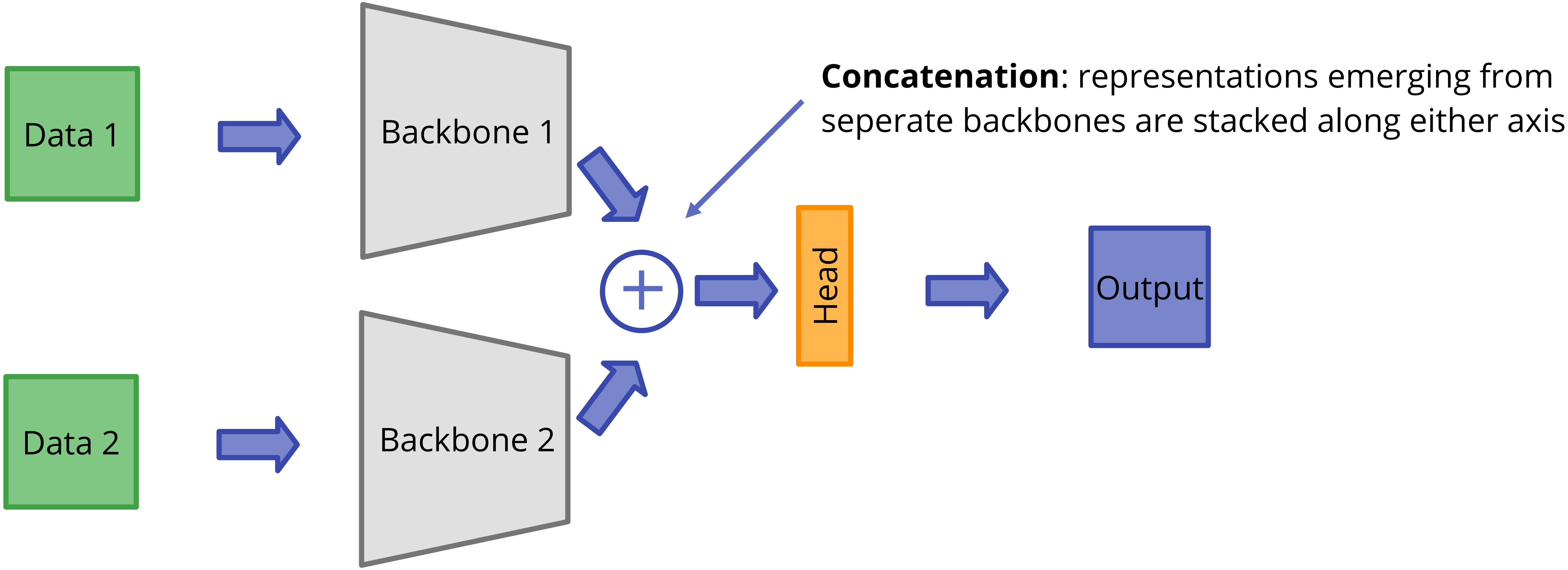
In Late Fusion, two (or more) data modalities are combined after passing through separate backbones:



Backbones might be completely separate, or have shared weights.

Late Fusion

In Late Fusion, two (or more) data modalities are combined after passing through separate backbones:



Backbones might be completely separate, or have shared weights.

Let's get our hands dirty

We will now implement a few Data Fusion methods in our first Notebook.

Specifically, we will implement the following:

- Supervised baseline model (Sentinel-2)
- Early Fusion (Sentinel1 and Sentinel-2)
- Early Fusion with blow-up patches (Sentinel-1, Sentinel-2 and Season)
- Late Fusion (Sentinel-1 and Sentinel-2)