

# Sampling and overfitting

AI for ecologists

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Paul Tresson

21/05/25

# Introduction

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## What do we want when modelling ?

- Understand things

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- Understand things
- **Predict things**

## What do we want when modelling ?

*“All models are wrong, but some are useful”*

George E. P. Box

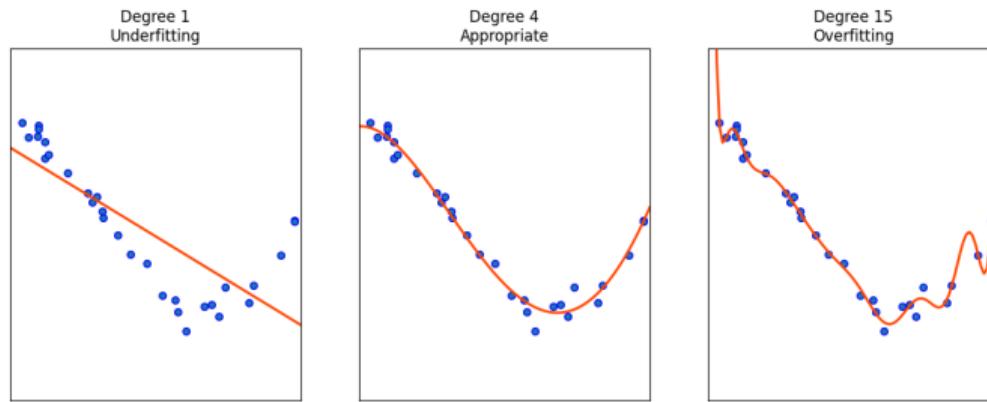
## What do we want when modelling ?

- **Robustness:** Useful when mistakes
- **Generalization:** Useful applied elsewhere

# Overfitting

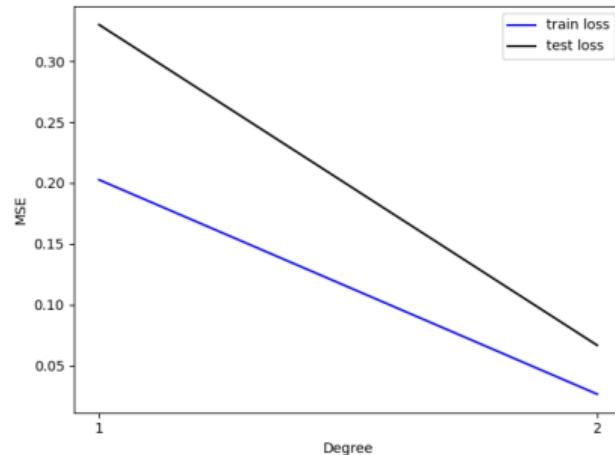
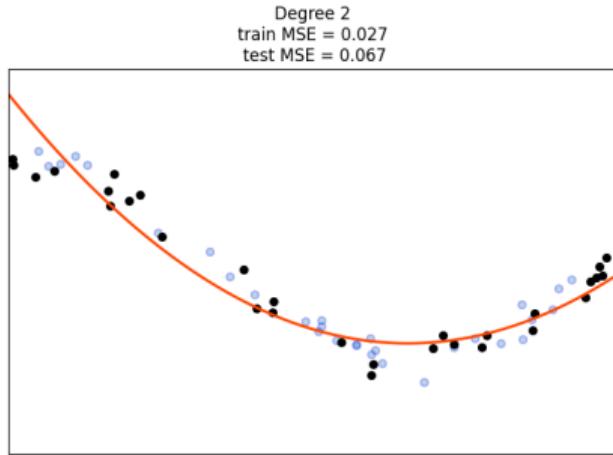
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# What is overfitting

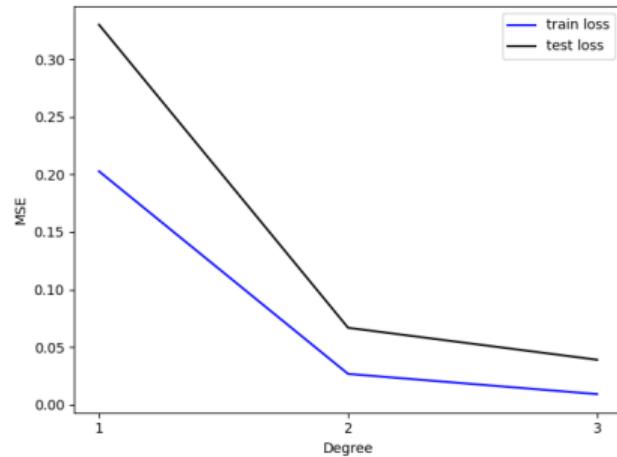
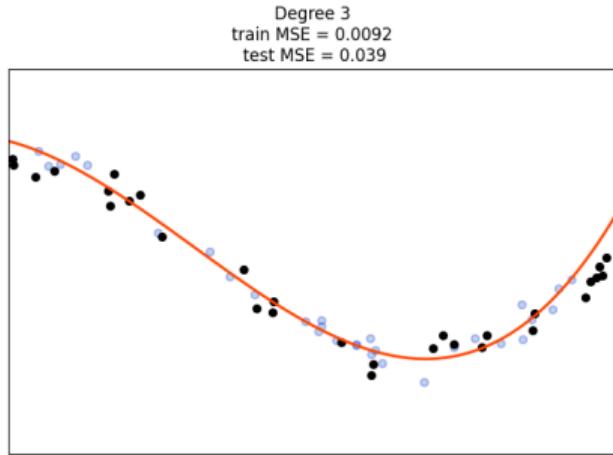


adapted from scikit-learn docs

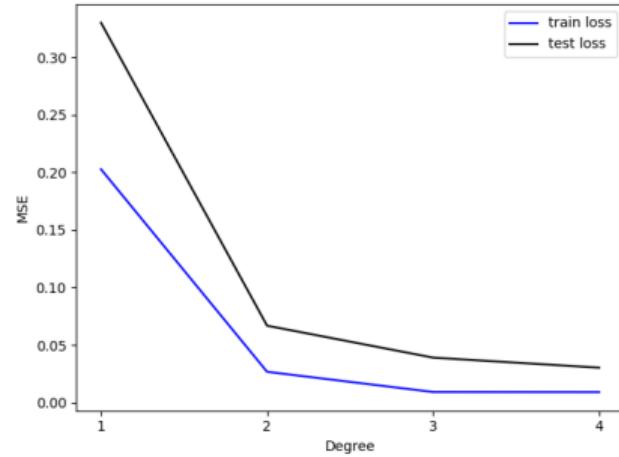
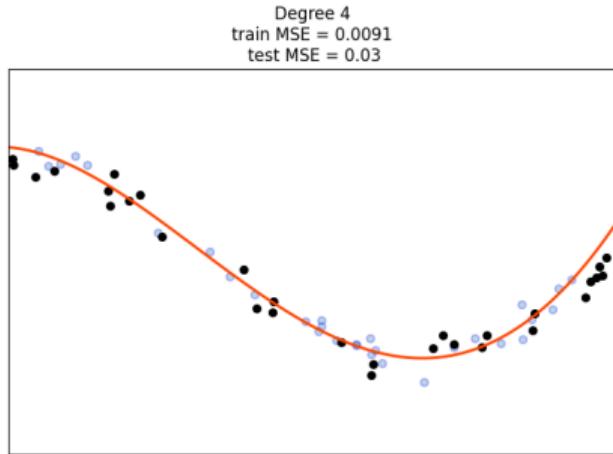
## Common tools and intuitions - Train/Test loss



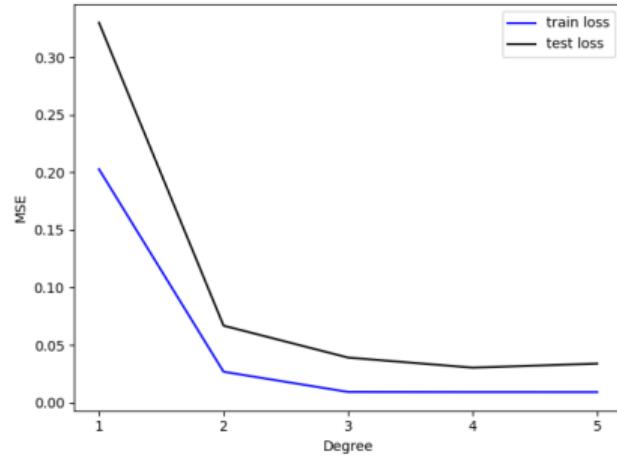
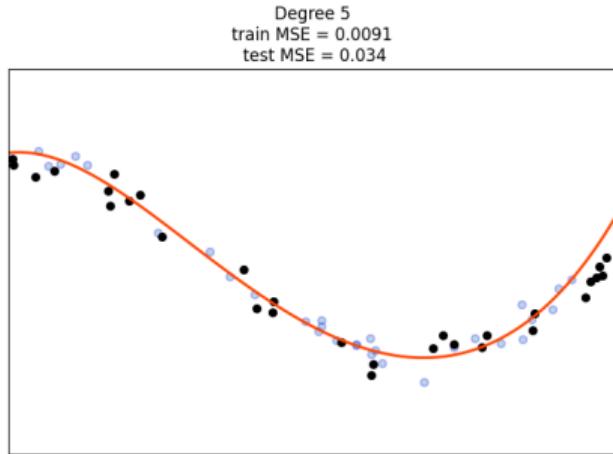
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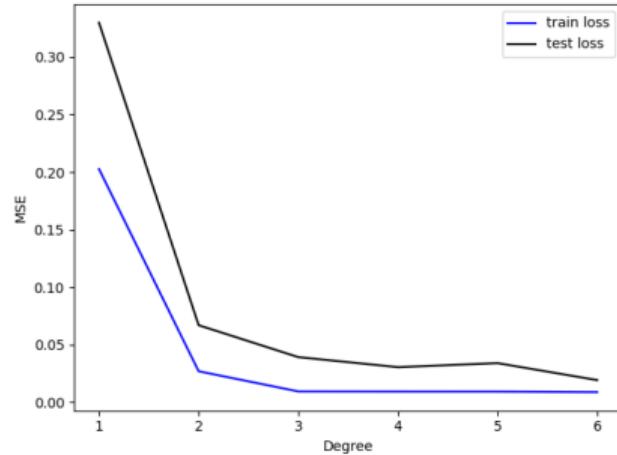
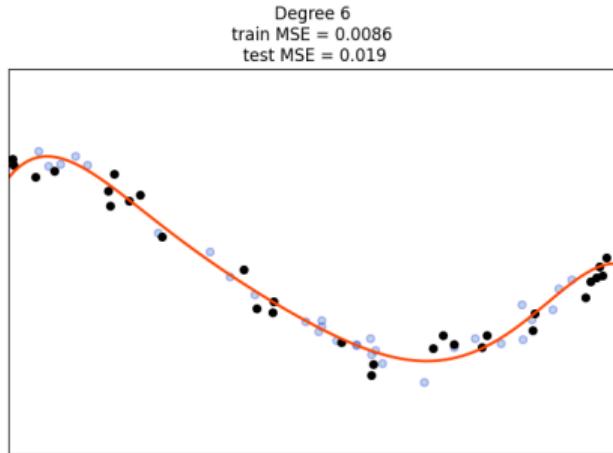
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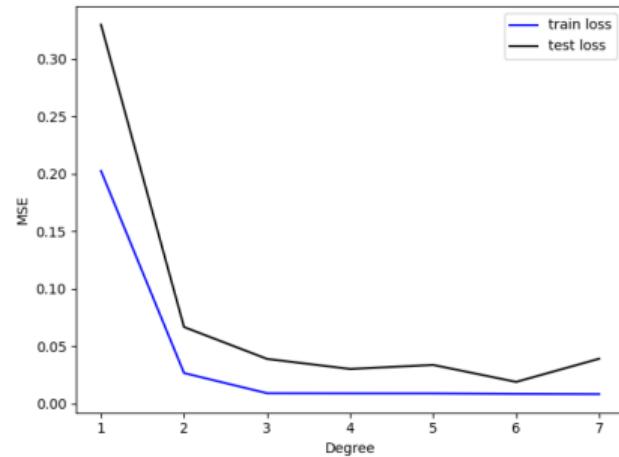
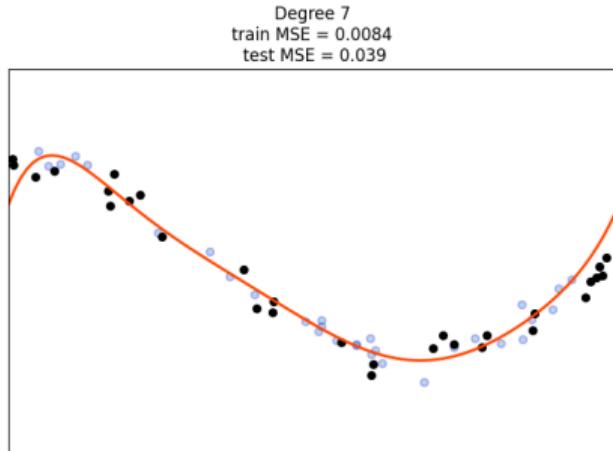
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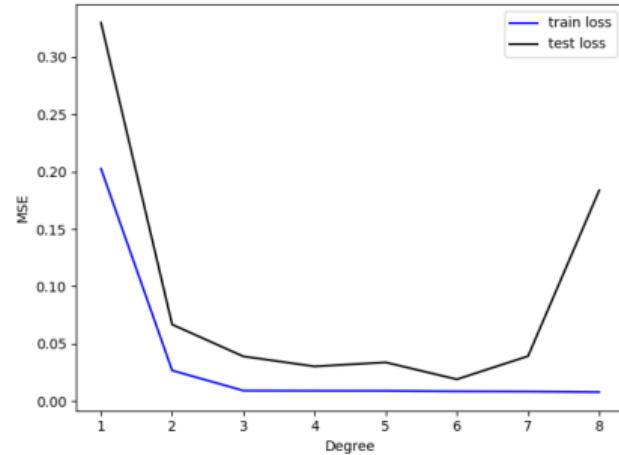
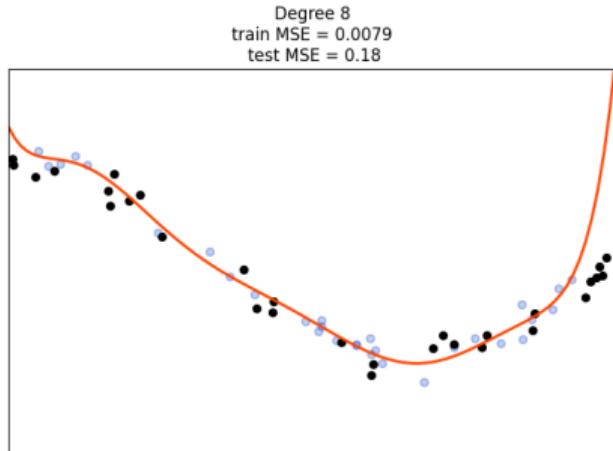
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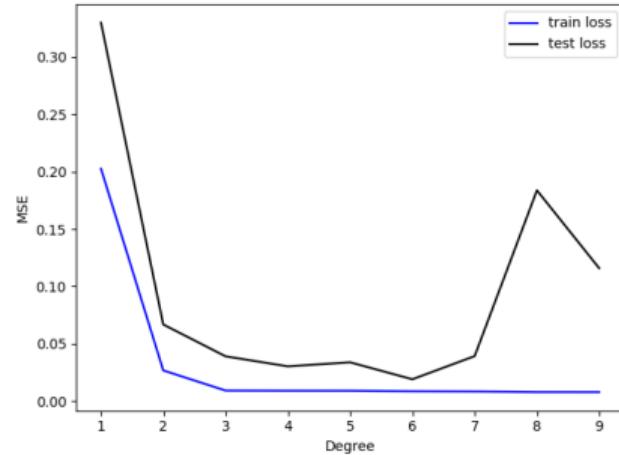
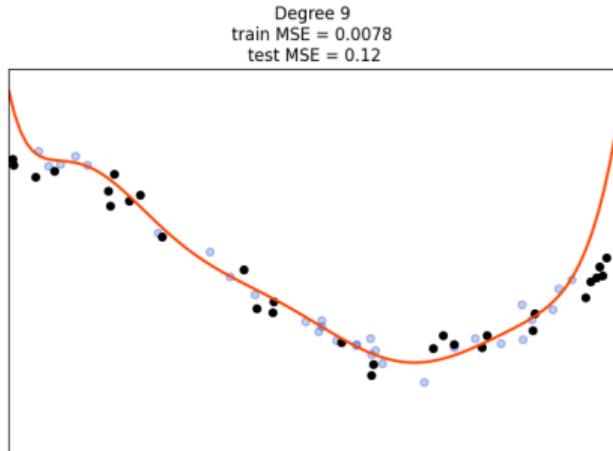
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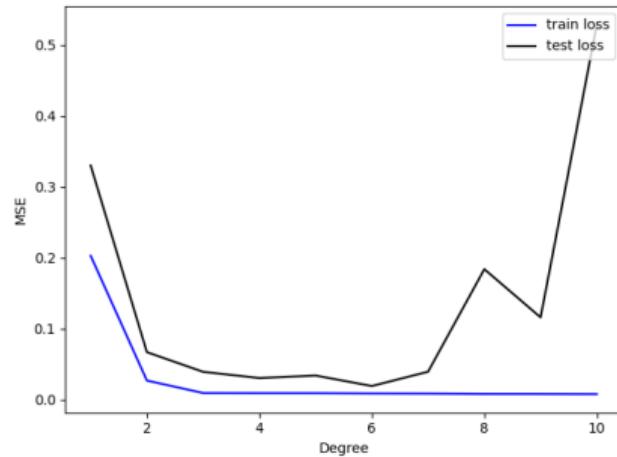
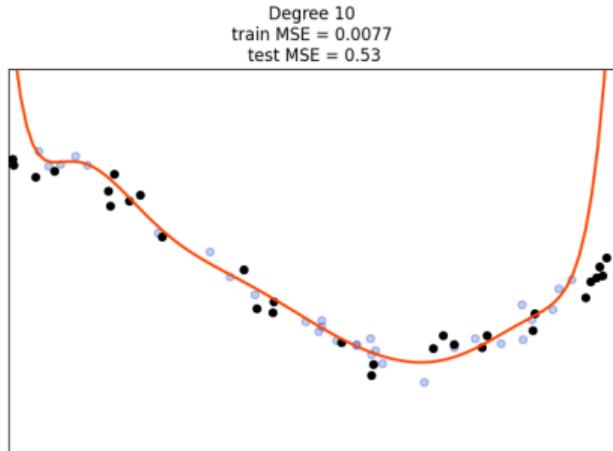
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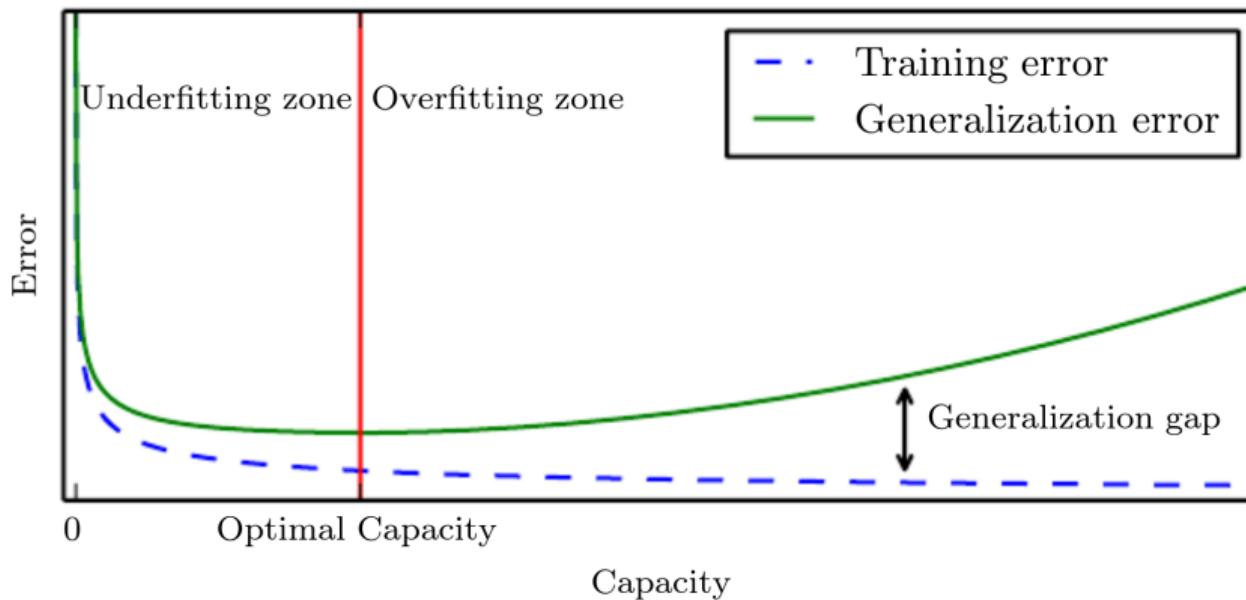


Figure from Goodfellow et al., 2016

## Common tools and intuitions - AIC/BIC

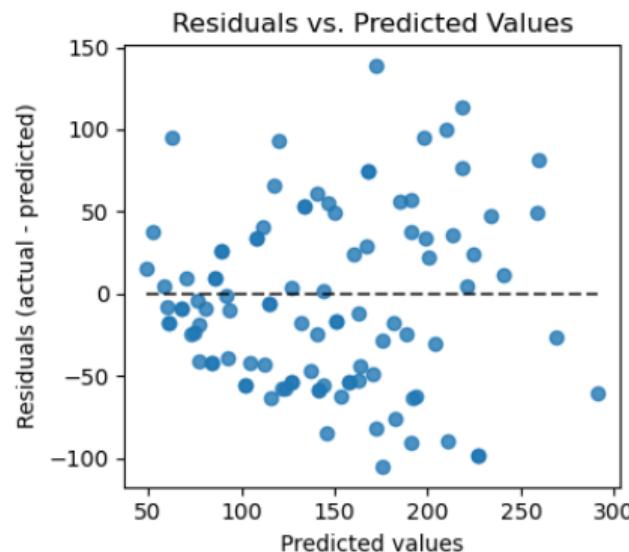
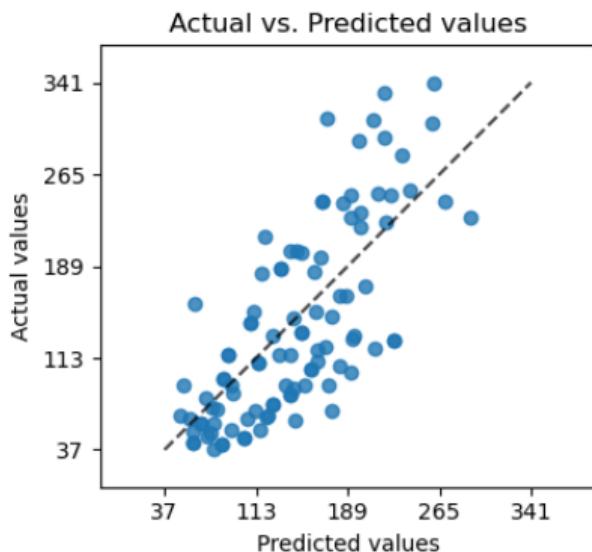
Akaike information criterion (AIC)

Bayesian information criterion (BIC)

Is the model parameter efficient ?

# Common tools and intuitions - Biases

Plotting cross-validated predictions



from scikit-learn docs

## And in Machine(/Deep) Learning ??

How many parameters to have

**Shrek learning botany starting from random noise ?**

# And in Machine(/Deep) Learning ??



$\approx 2.5B ?$

# Root Causes

Too many parameters

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Too many parameters

Too little training data

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Too many parameters

Too little training data

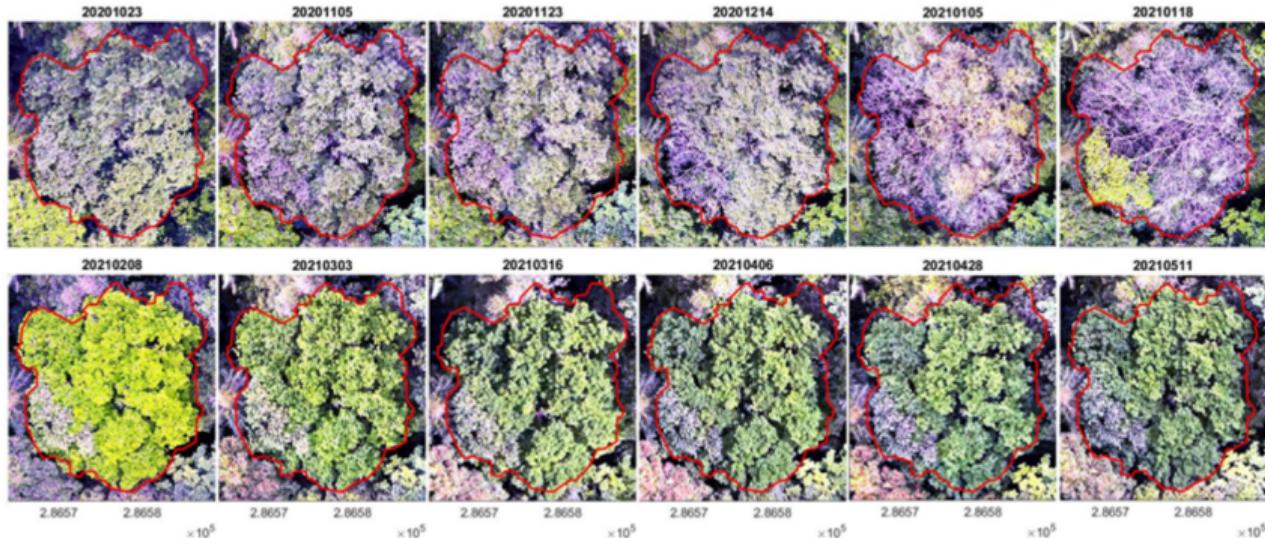
(bad) training data

## Illustrated examples in Ecology

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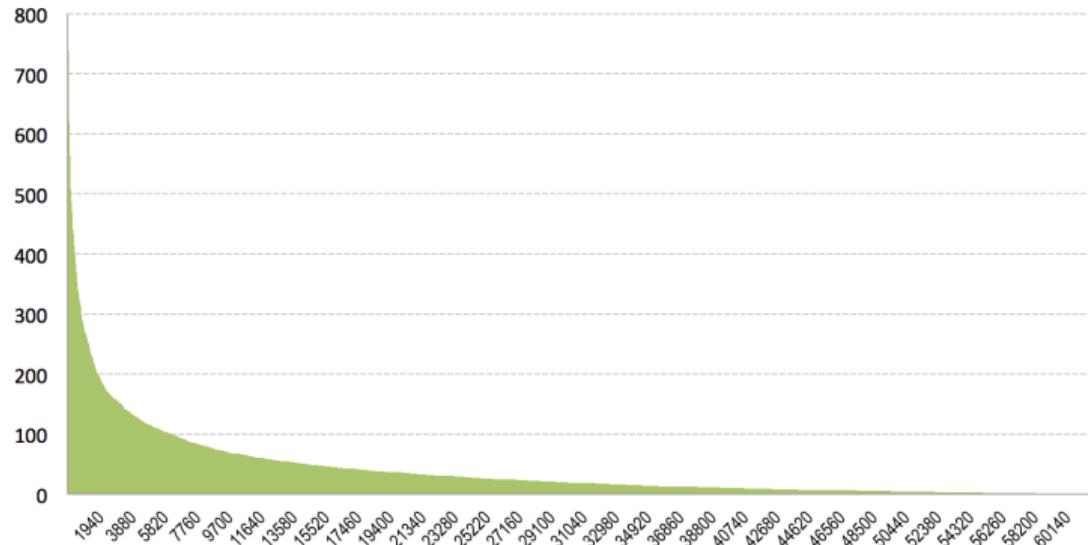
# Constraints in ecology

Data from the real world is noisy,



# Constraints in ecology

Data from the real world is noisy, unbalanced,



## Constraints in ecology

Data from the real world is noisy, unbalanced, hard to collect,



# Constraints in ecology

Data from the real world is noisy, unbalanced, hard to collect, hard to interpret.

Select all images with an Orange.

Verify

# Constraints in ecology

Data from the real world is noisy, unbalanced, hard to collect, hard to interpret.

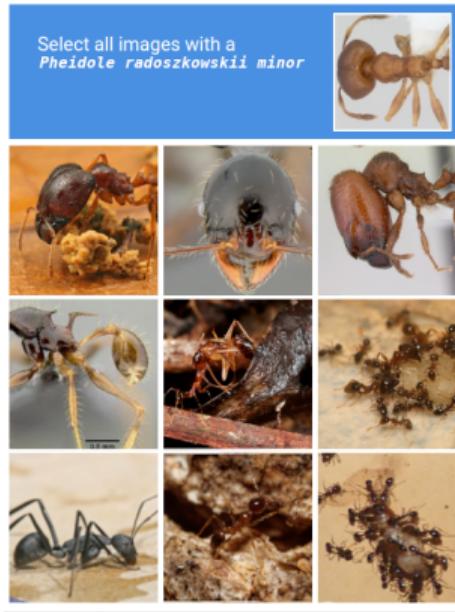
Select all images with an Orange.

C    Verify

# Constraints in ecology

Data from the real world is noisy, unbalanced, hard to collect, hard to interpret.

Select all images with a  
*Pheidole radoszkowskii minor*



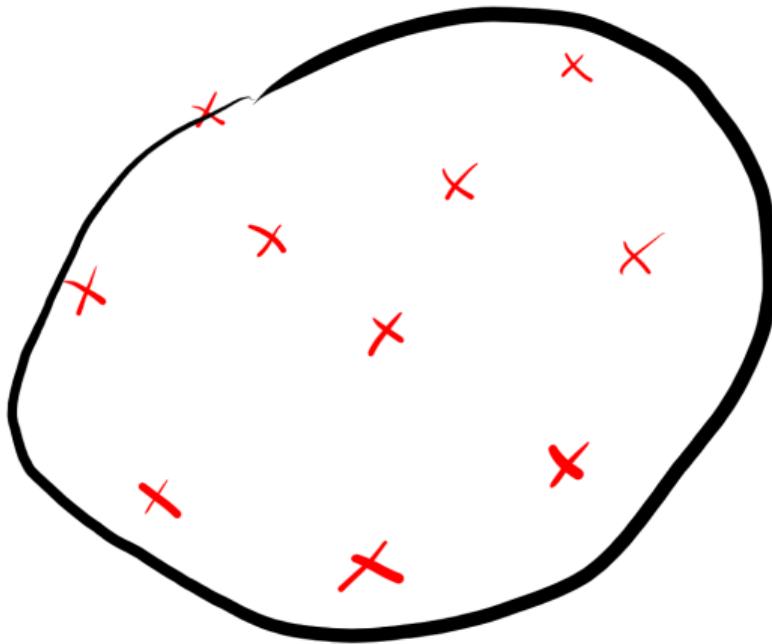
The grid contains 12 images arranged in three rows of four. The first image in the top row is a close-up of a single ant. The second image is a close-up of an ant's head. The third image is a side view of an ant. The fourth image is a cluster of small ants. The fifth image is a side view of an ant. The sixth image is a close-up of an ant's head. The seventh image is a cluster of small ants. The eighth image is a side view of an ant. The ninth image is a close-up of an ant's head. The tenth image is a cluster of small ants. The eleventh image is a side view of an ant. The twelfth image is a close-up of an ant's head.



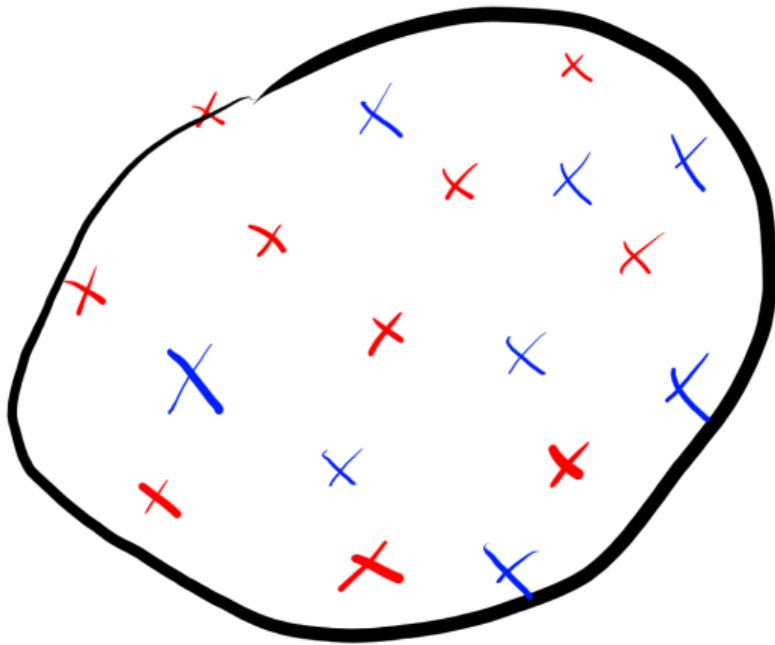
Verify



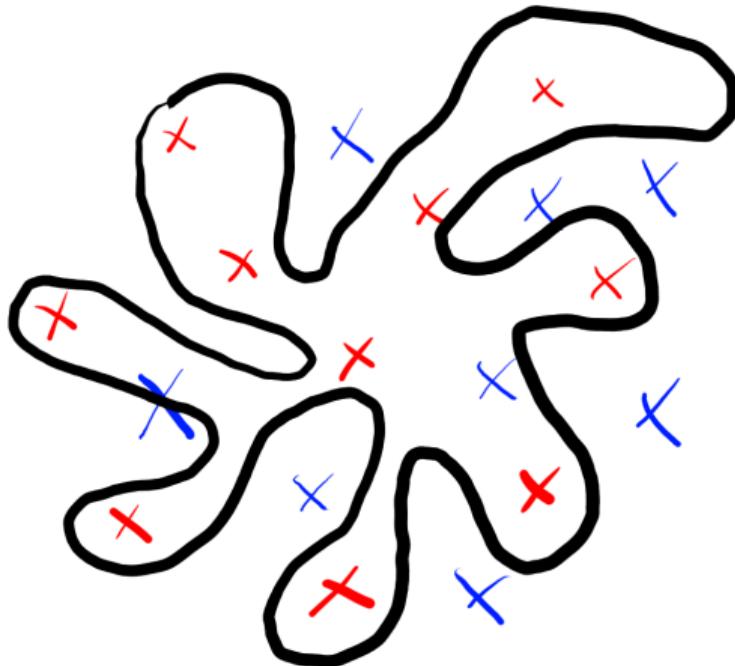
Train set



A good fitted model



Test set

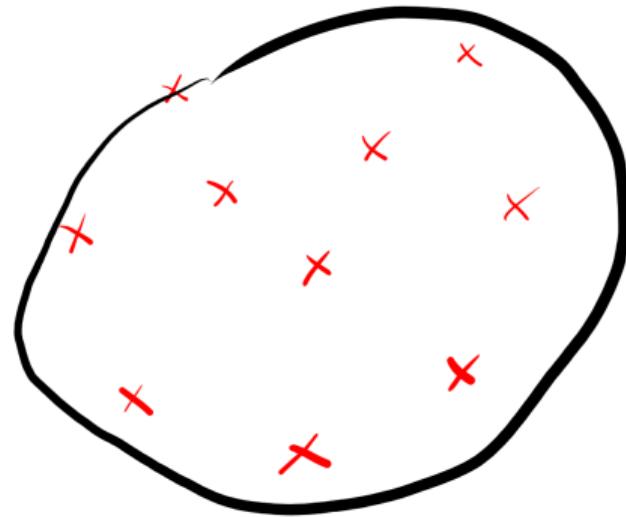


An overfitted model

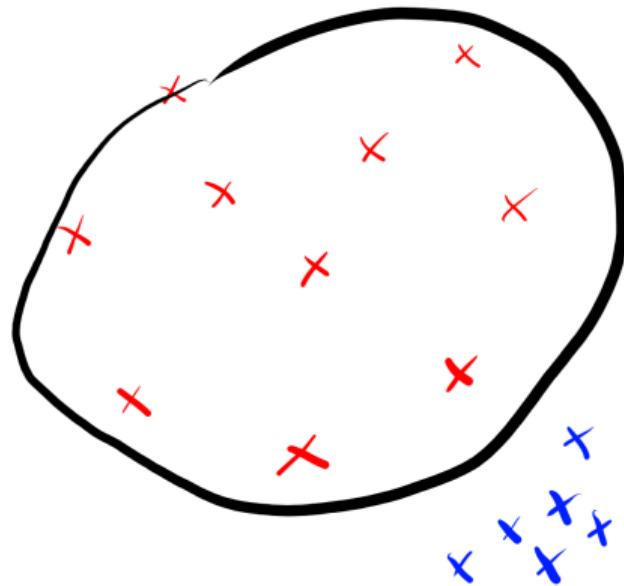
## Biases in the train set



## Biases in the train set



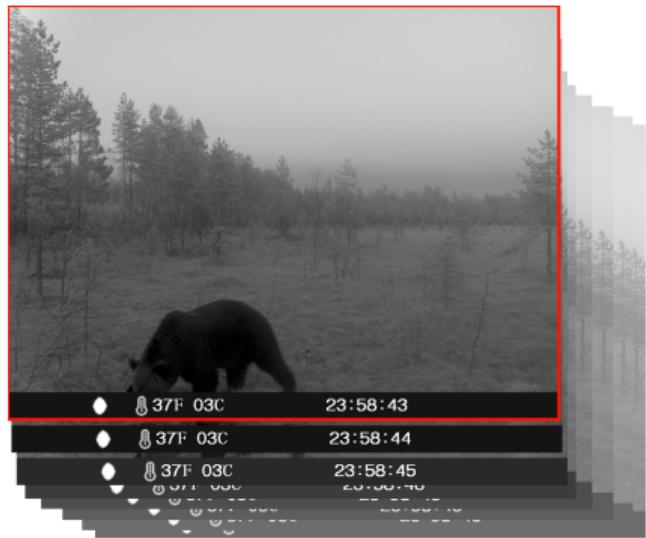
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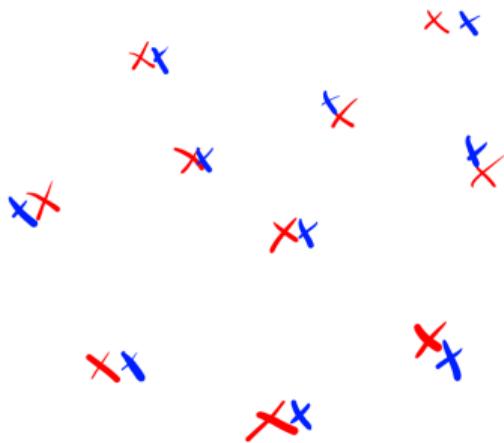
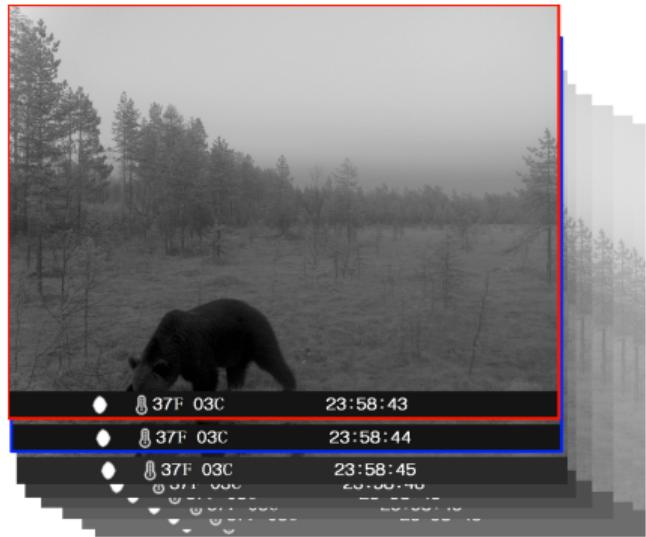
## Biases in the train set - autocorrelation



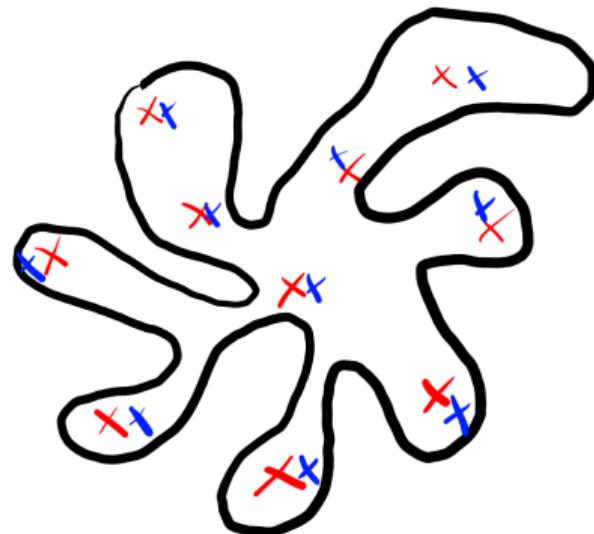
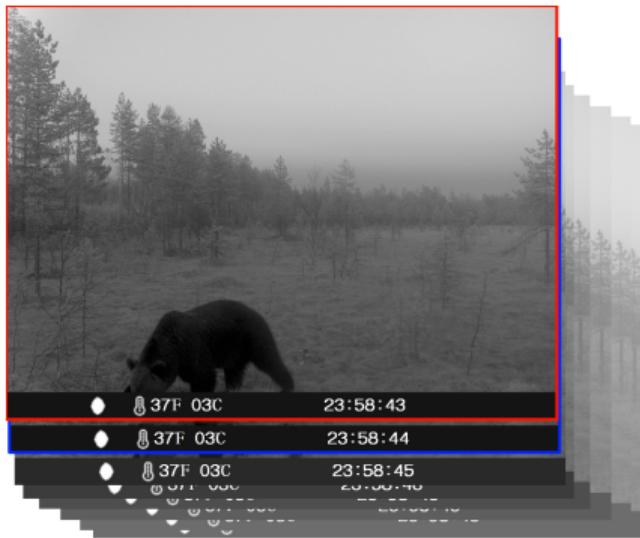
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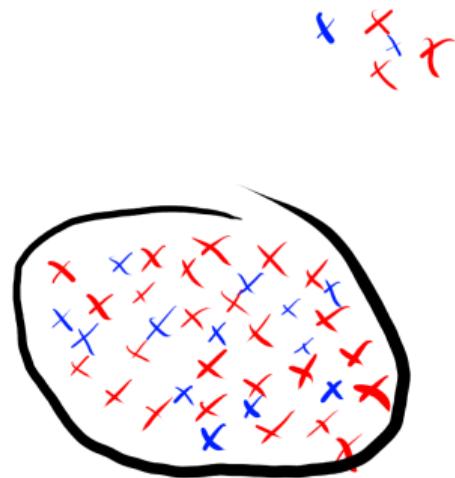
## Unbalanced data



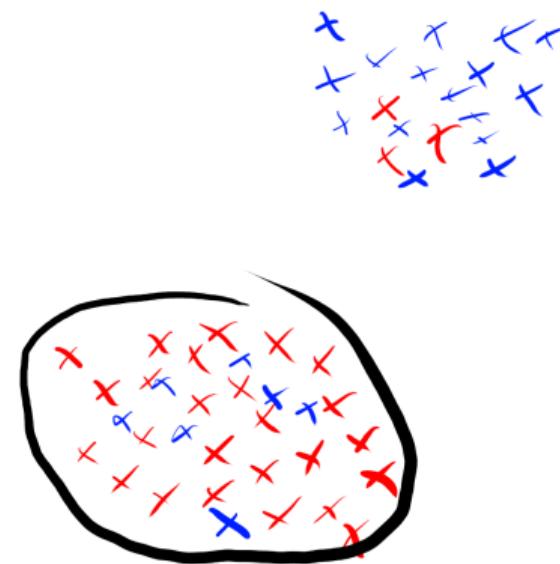
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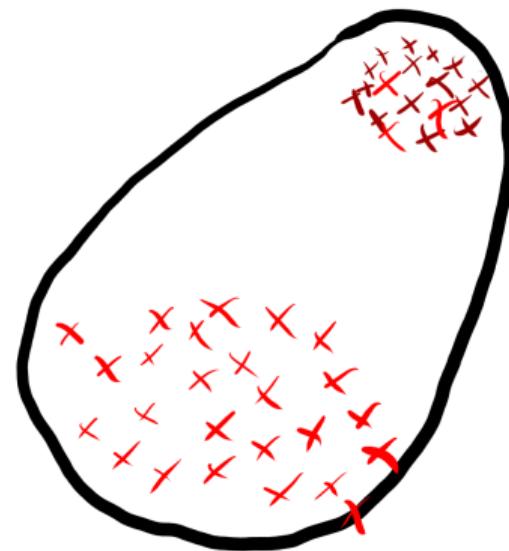
## Deal with unbalanced data

- Oversample ?



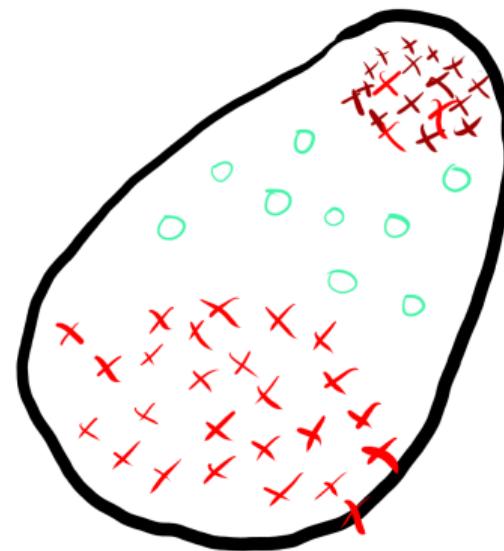
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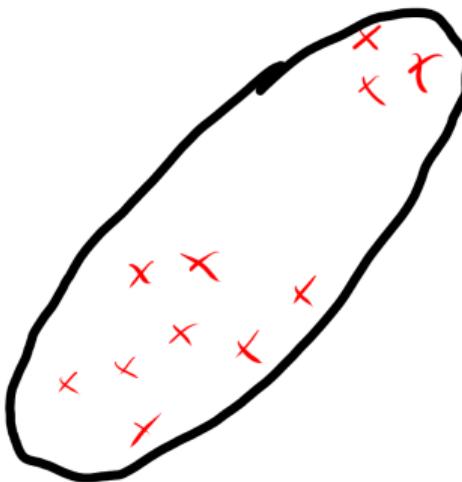
## Deal with unbalanced data

- Oversample ?
- Undersample/saturate ?



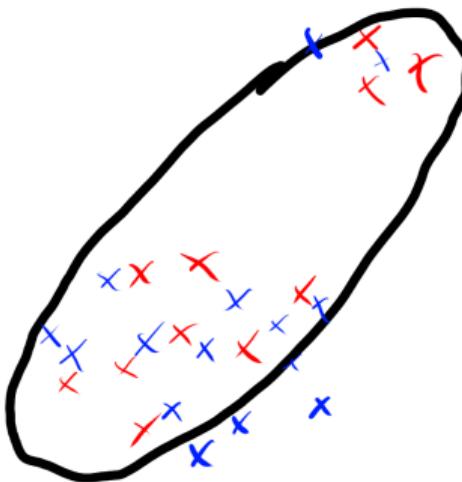
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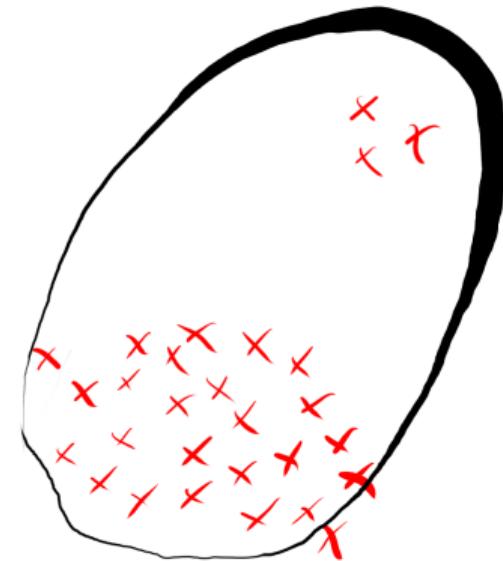
## Deal with unbalanced data

- Oversample ?
- Undersample/saturate ?



## Deal with unbalanced data

- Oversample ?
- Undersample/saturate ?
- Adapt loss ?



## Deal with lack of data

- Data augmentation



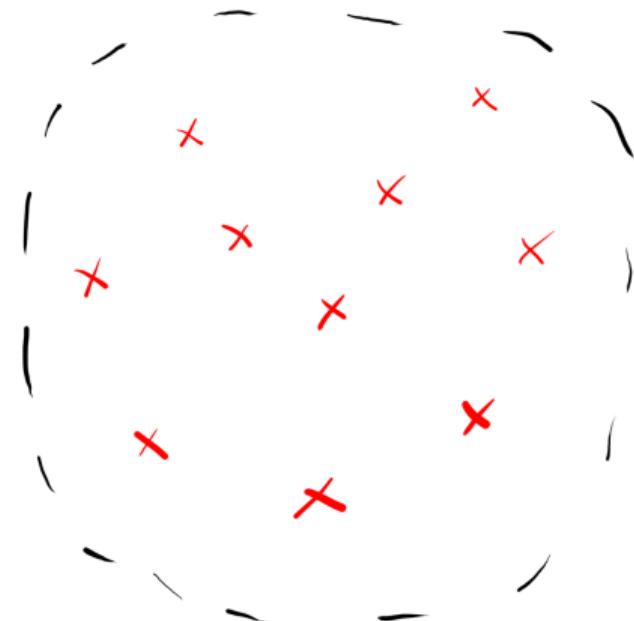
## Deal with lack of data

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## Deal with lack of data

- Data augmentation
- Pretrained model



## Deal with lack of data

- Data augmentation
- Pretrained model
- ... **collect more data**

# Play with your model

- Dropout
- Pruning
- Ablation studies
- Ensembles

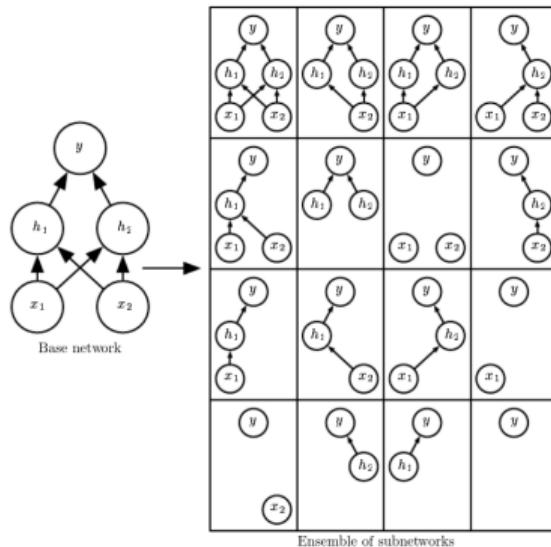


Figure from Goodfellow et al., 2016

**Need to be very carefull on how to evaluate**

## How to sample and evaluate ?

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## Random split ?

“random split training validation 80/20”

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For the uncurated dataset, we randomly sample 142 million images

Oquab et al., 2023

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“random split training validation 80/20”

For the uncurated dataset, we randomly sample 142 million images

Oquab et al., 2023

Works for huge DL papers, maybe not for you

# Cross-validation

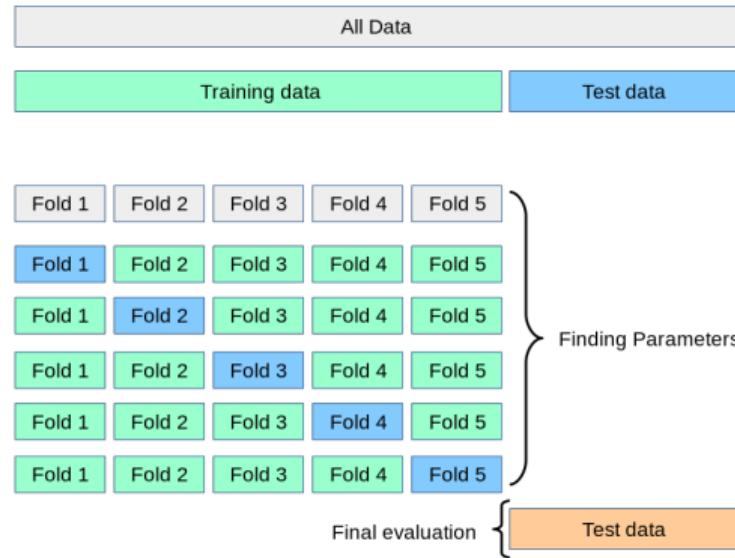


Figure from scikit-learn docs

## Cross-validation

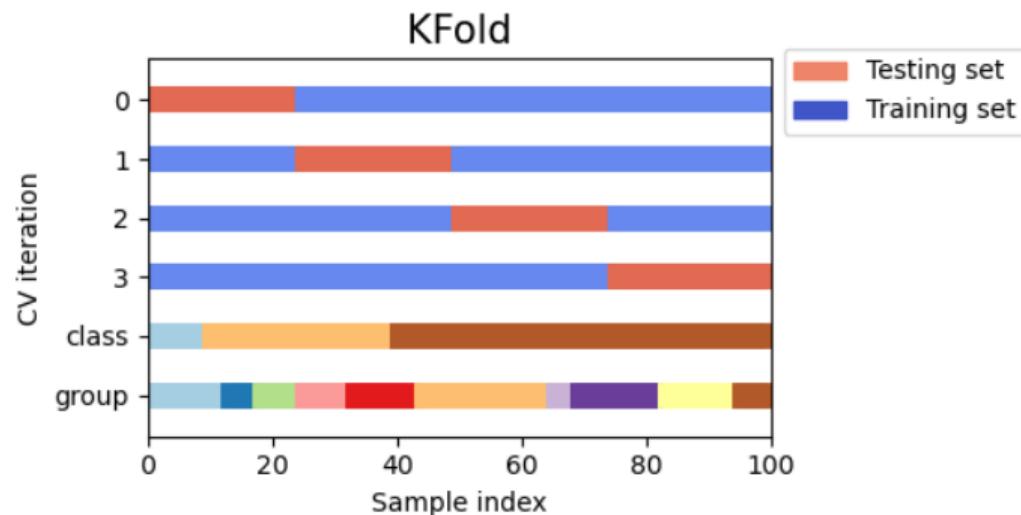


Figure from scikit-learn docs

## Cross-validation

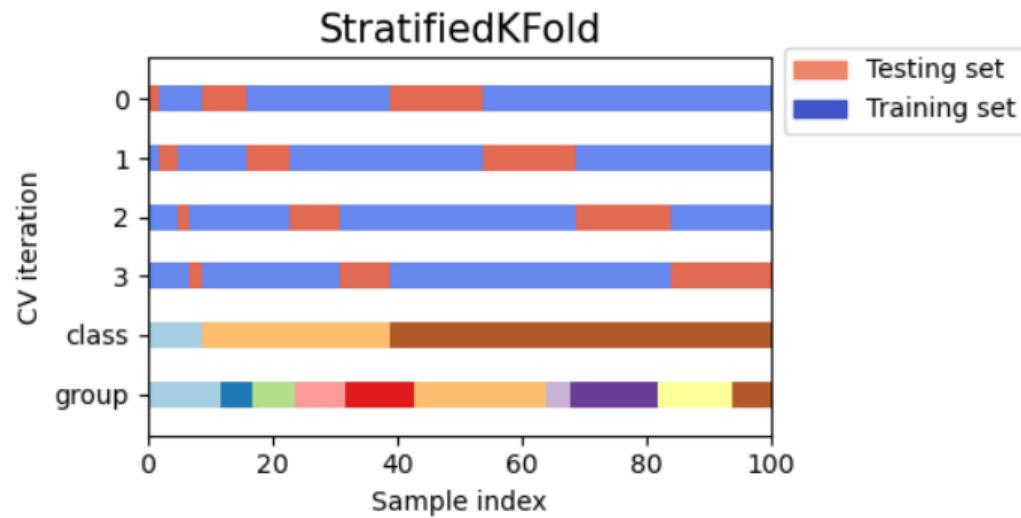
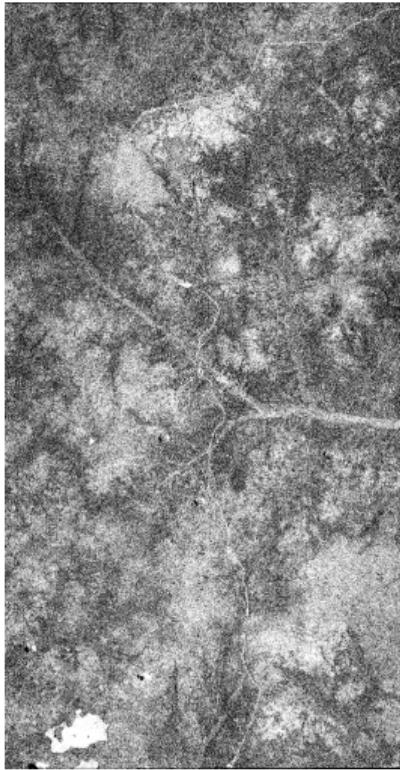
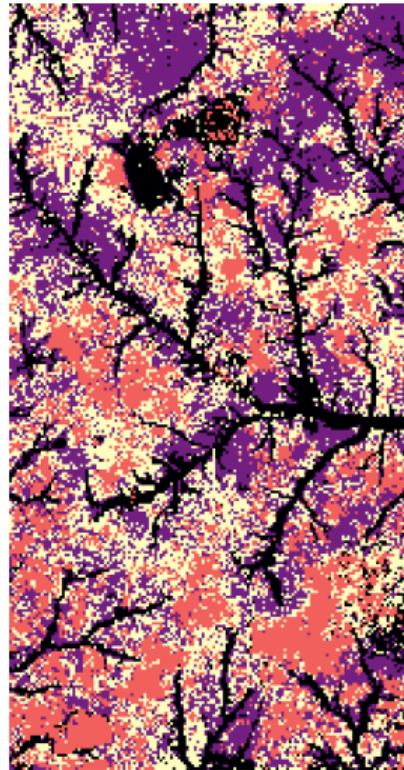


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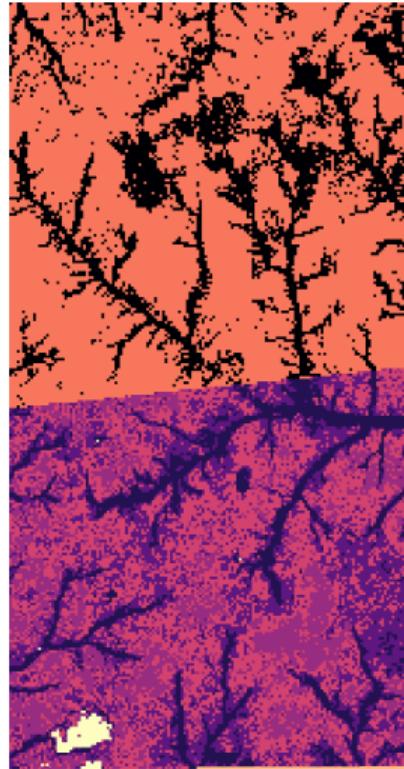
## Case study : Spatial cross-validation



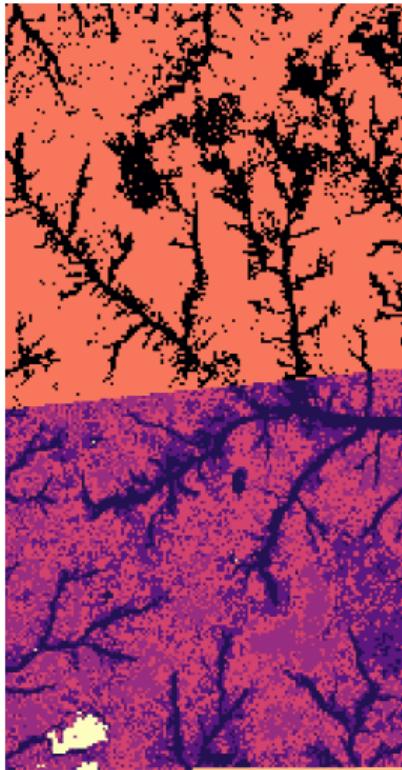
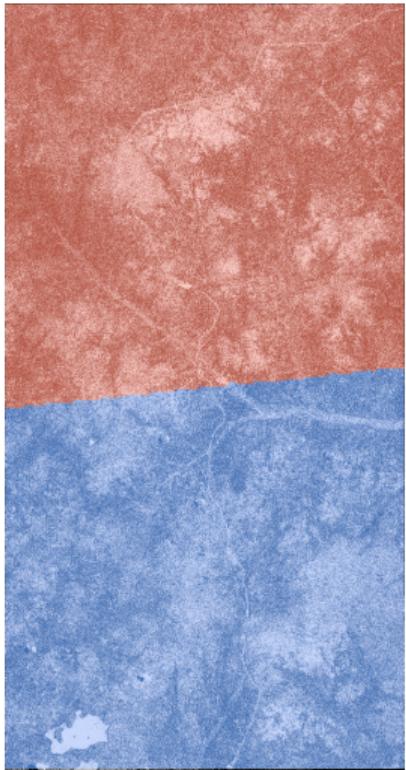
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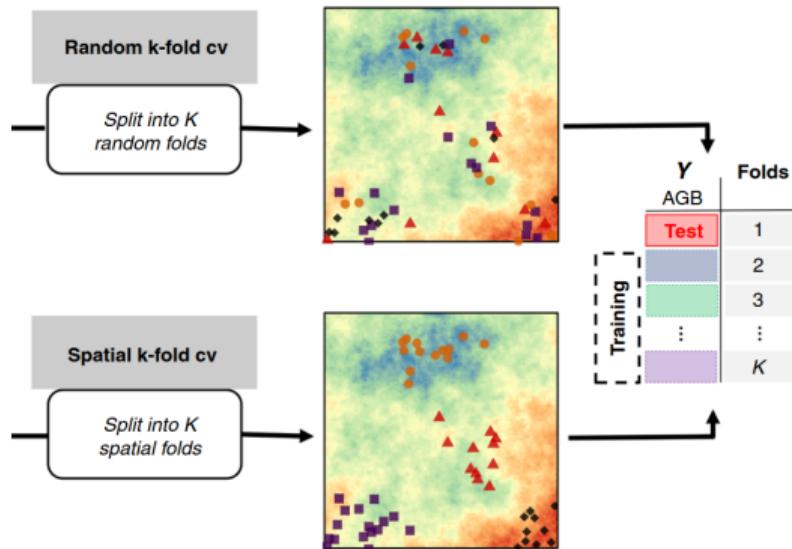
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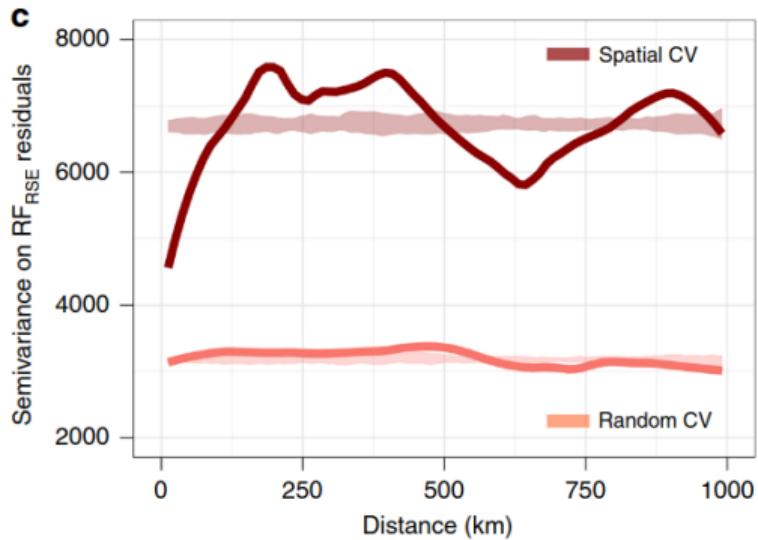


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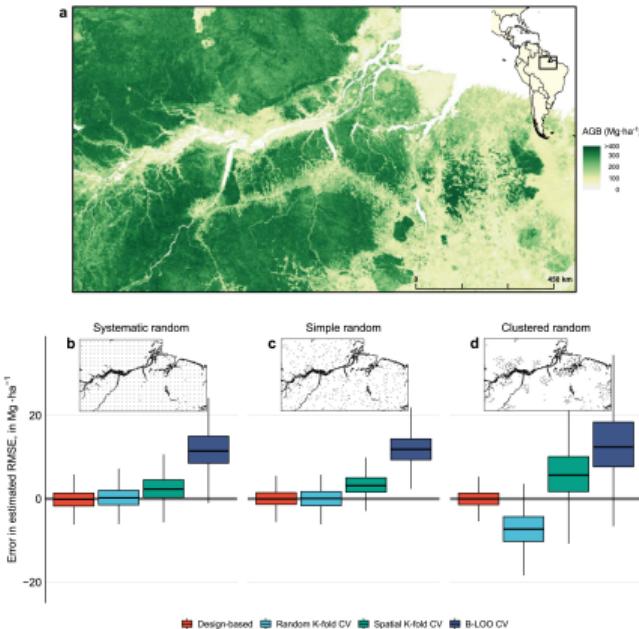
See. Ploton et al., 2020

## Case study : Spatial cross-validation



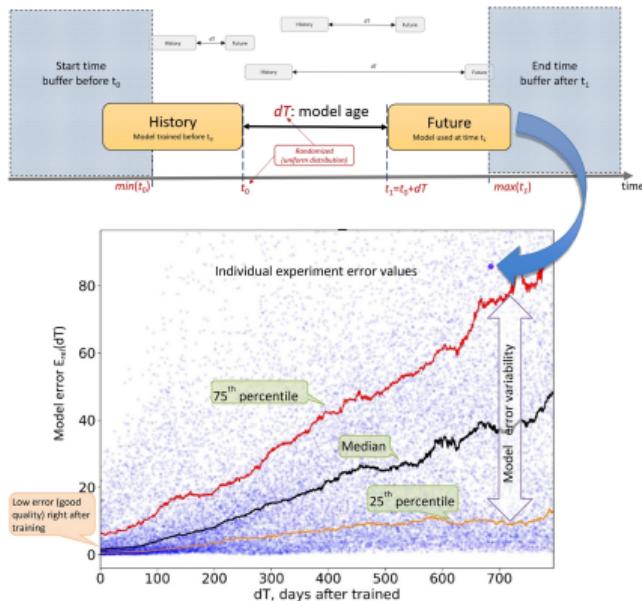
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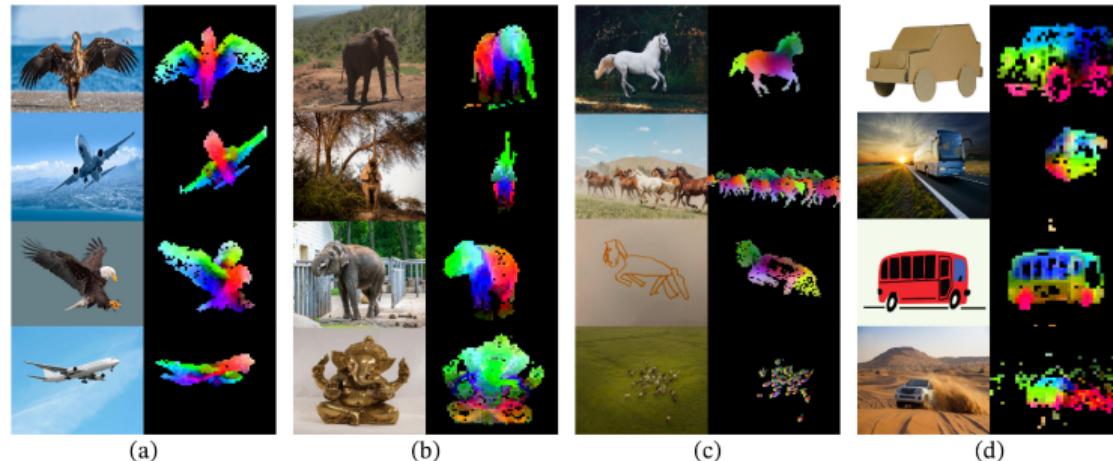
See. Wadoux et al., 2021

# Case study : Aging models ?



See. Vela et al., 2022

# Perspective : Foundation models ?



See. Oquab et al., 2023

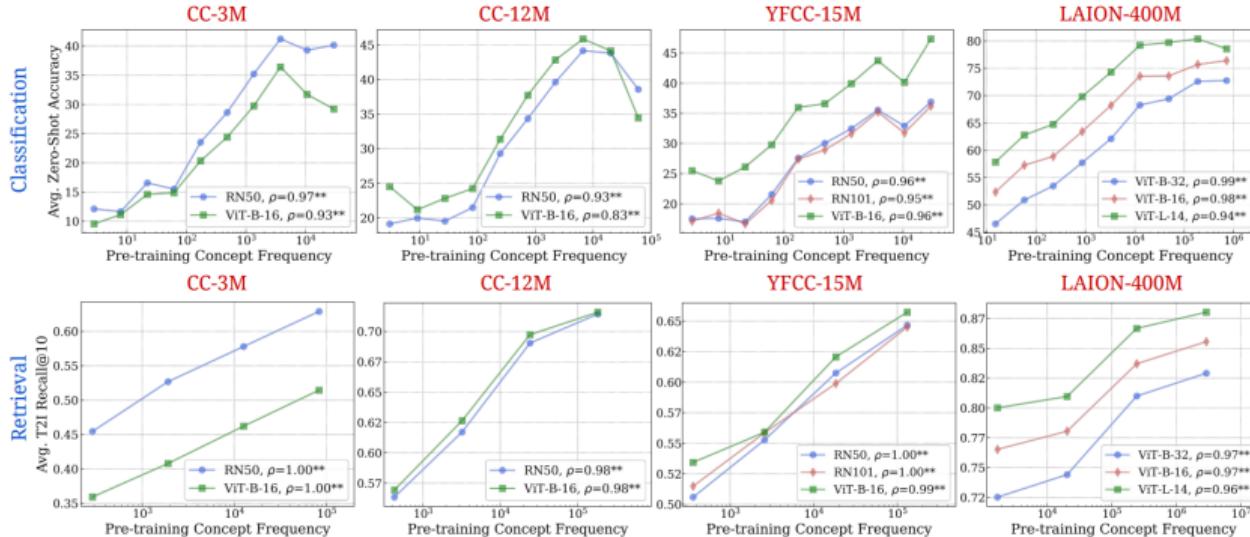
# Perspective : Foundation models ?



A photograph of  
[Anne Graham  
Lotz](#) included in  
the training set  
of [Stable  
Diffusion](#), a [text-  
to-image model](#)

An image generated by  
Stable Diffusion using  
the prompt "Anne  
Graham Lotz"

# Perspective : Foundation models ?



See. Udandarao et al., 2024

## Usefull ressources

- scikit-learn docs !

**Thanks for you attention !**

**Let's practice !**

## References i

- Goodfellow, Ian, Yoshua Bengio, Aaron Courville, and Yoshua Bengio (2016). **Deep learning**. Vol. 1. 2. MIT press Cambridge.
- Oquab, Maxime et al. (2023). “**Dinov2: Learning robust visual features without supervision**”. In: *arXiv preprint arXiv:2304.07193*.
- Ploton, Pierre et al. (2020). “**Spatial validation reveals poor predictive performance of large-scale ecological mapping models**”. In: *Nature communications* 11.1, p. 4540.
- Udandarao, Vishaal et al. (2024). “**No zero-shot without exponential data: Pretraining concept frequency determines multimodal model performance**”. In: *The Thirty-eighth Annual Conference on Neural Information Processing Systems*.

## References ii

Vela, Daniel et al. (2022). “**Temporal quality degradation in AI models**”. In: *Scientific reports* 12.1, p. 11654.

Wadoux, Alexandre MJ-C, Gerard BM Heuvelink, Sytze De Bruin, and Dick J Brus (2021). “**Spatial cross-validation is not the right way to evaluate map accuracy**”. In: *Ecological Modelling* 457, p. 109692.