

# 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

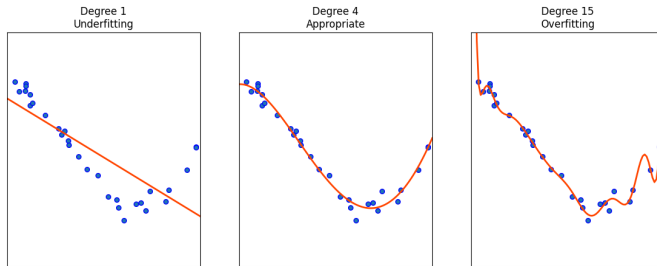
# What do we want when modelling ?

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

# Overfitting

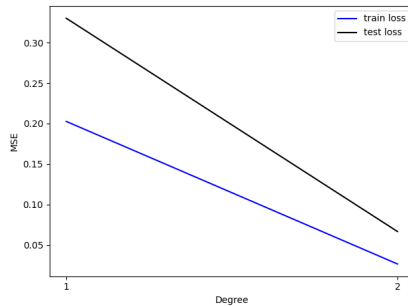
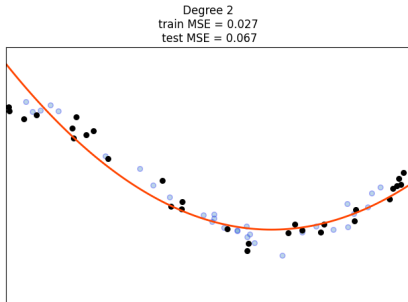
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# What is overfitting

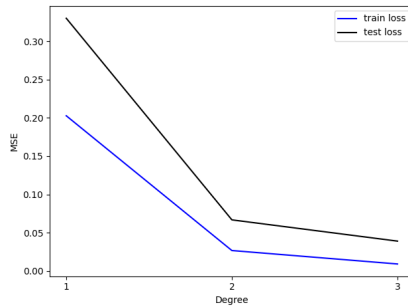
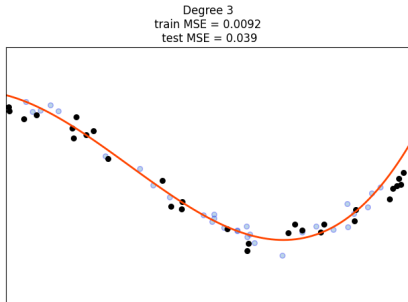


adapted from scikit-learn docs

# Common tools and intuitions - Train/Test loss

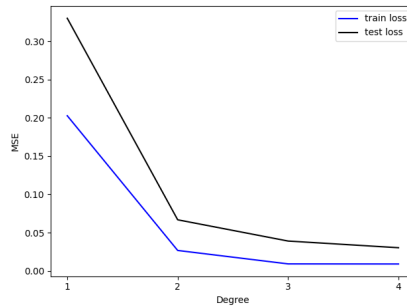
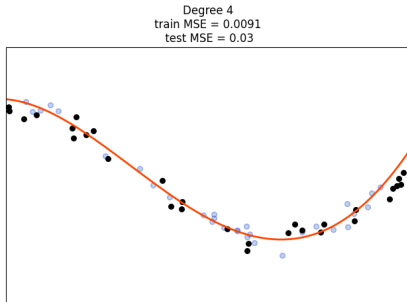


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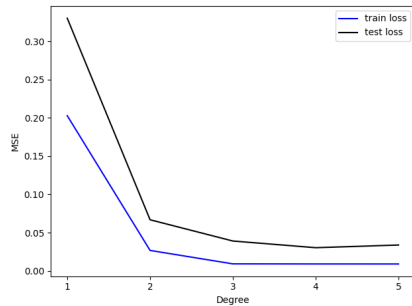
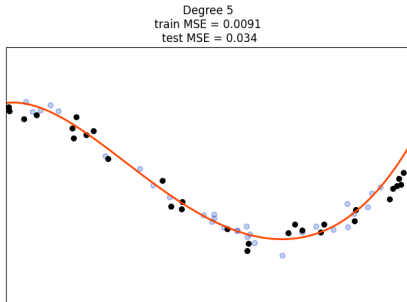




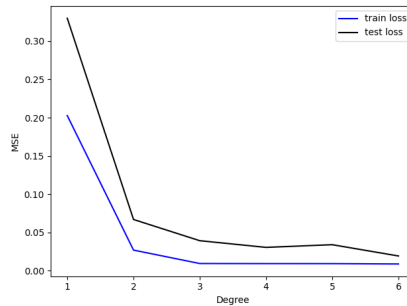
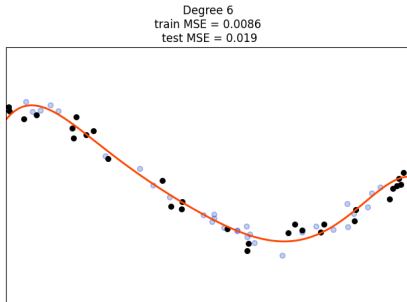
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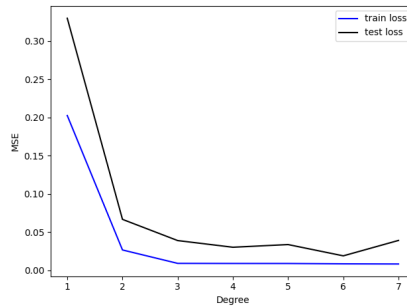
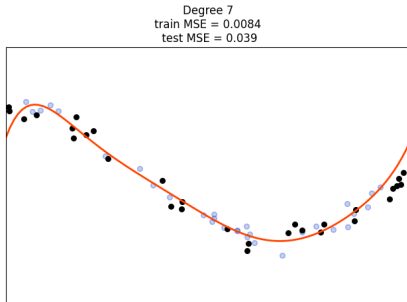
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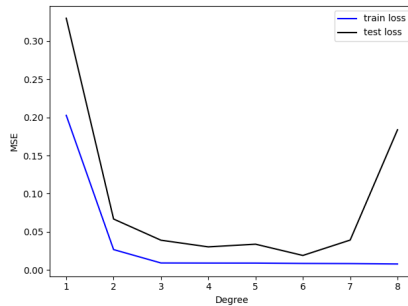
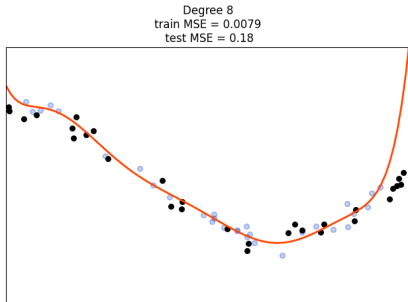
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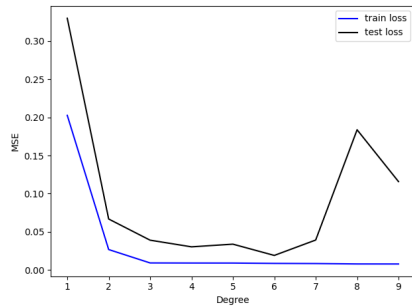
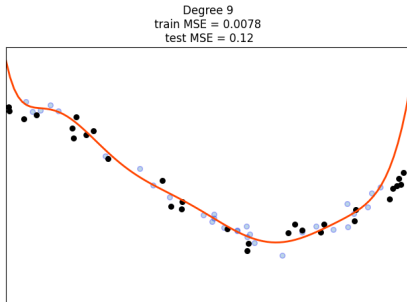
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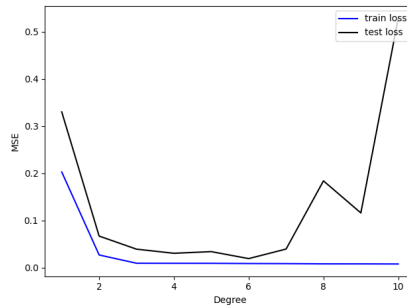
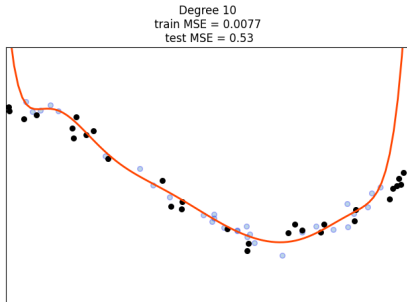
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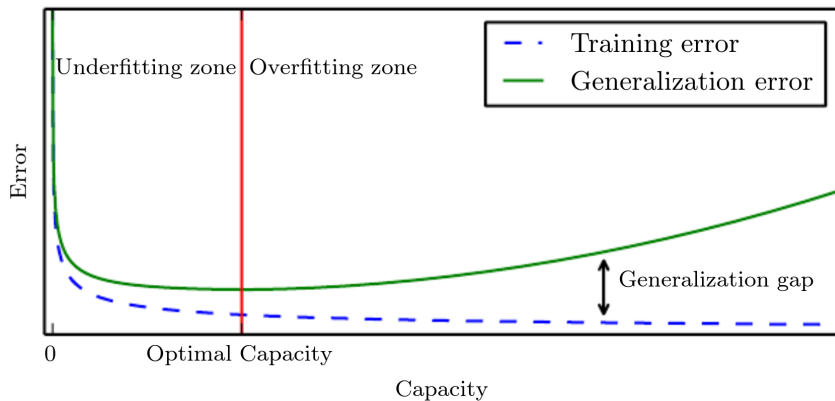


Figure from Goodfellow et al., 2016



## Common tools and intuitions - AIC/BIC

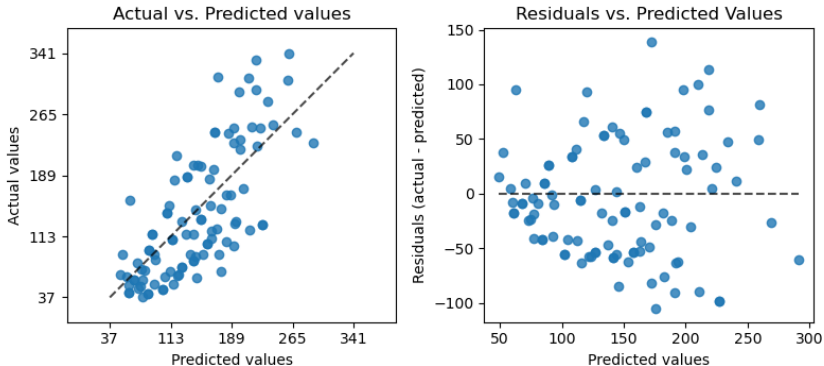
**Akaike information criterion (AIC)**

**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**

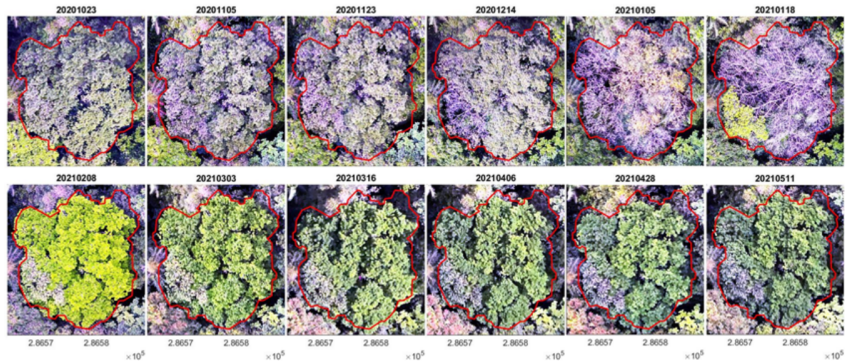
## Illustrated examples in Ecology

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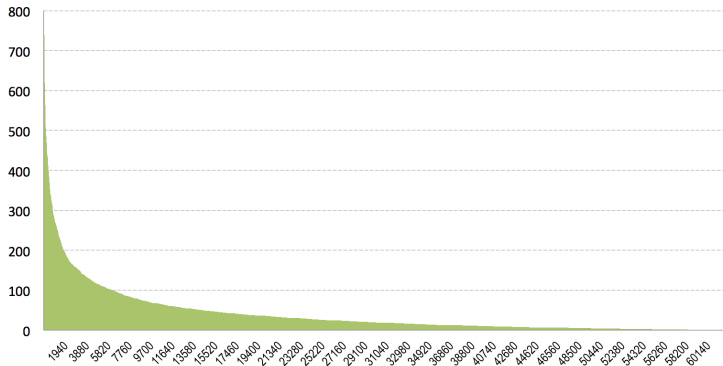
# Constraints in ecology

Data from the real world is noisy,



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Data from the real world is noisy, unbalanced,



## Constraints in ecology

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



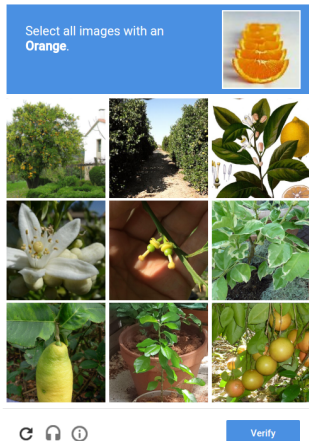
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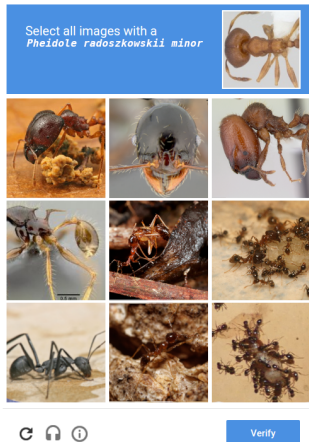
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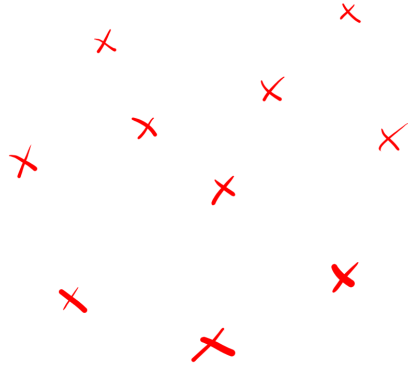
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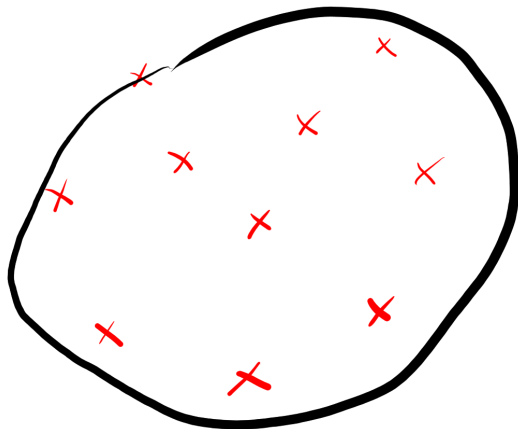
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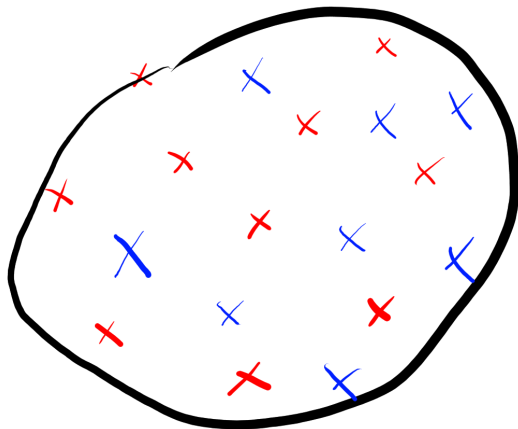


Train set

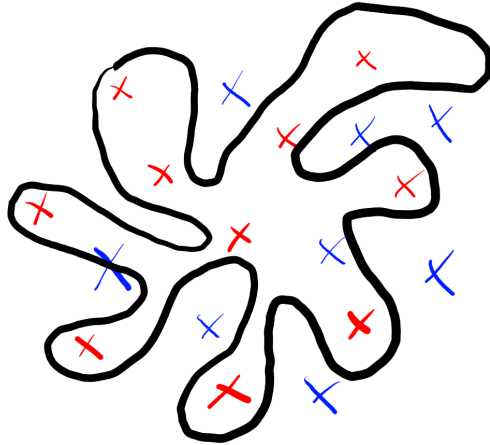


A good fitted model





Test set

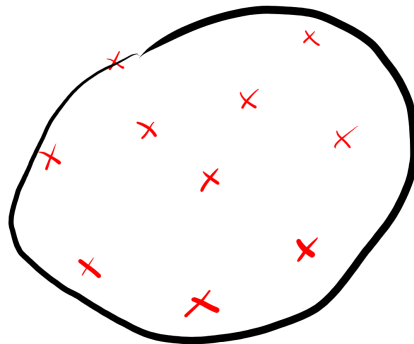


An overfitted model

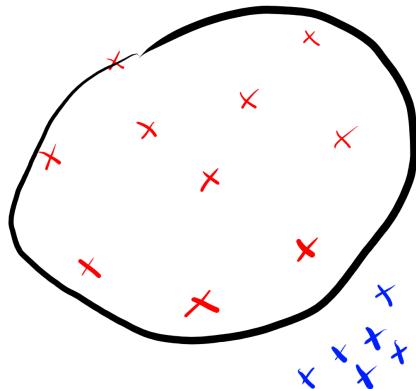
# Biases in the train set



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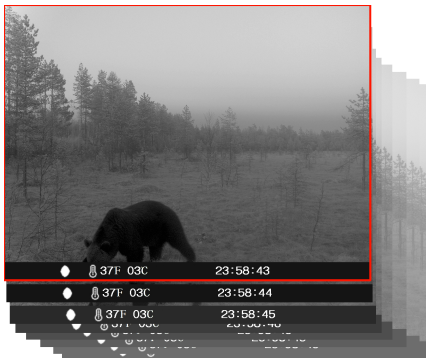
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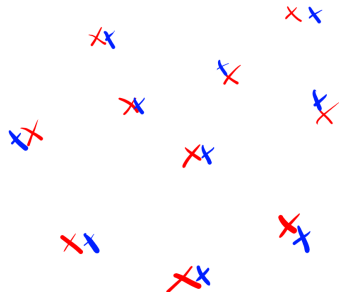
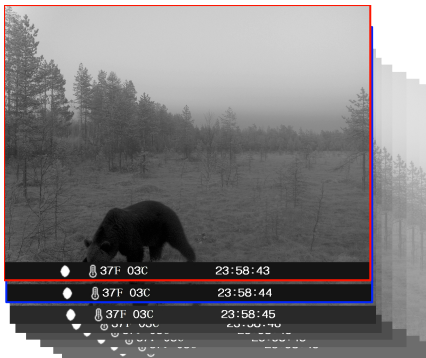
## Biases in the train set - autocorrelation



## Biases in the train set - autocorrelation

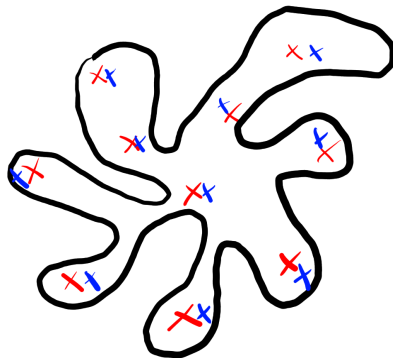


## Biases in the train set - autocorrelation

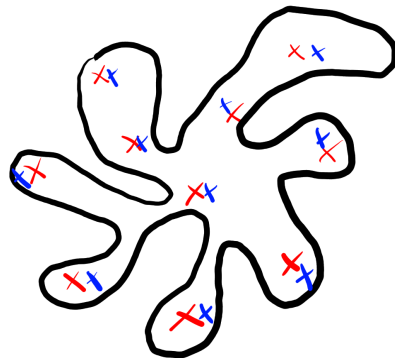




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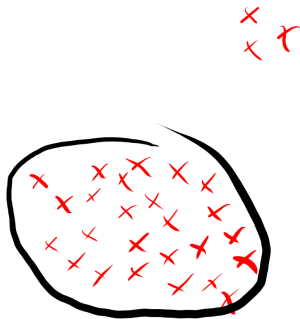
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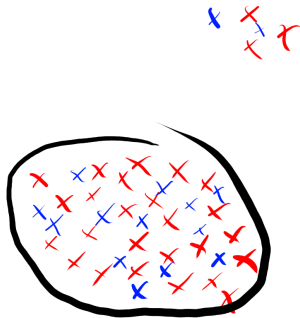
## Unbalanced data



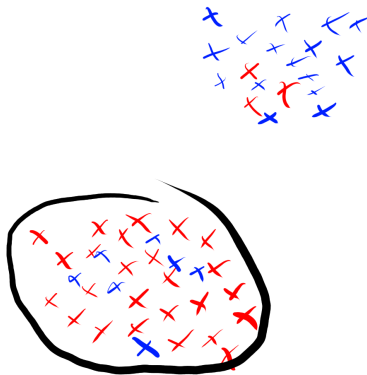
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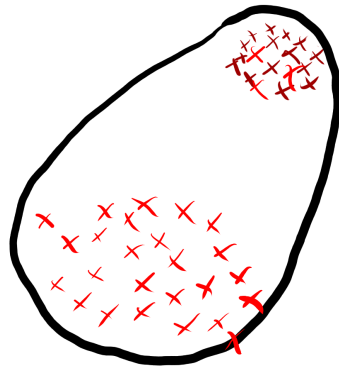
# Deal with unbalanced data

- Oversample ?



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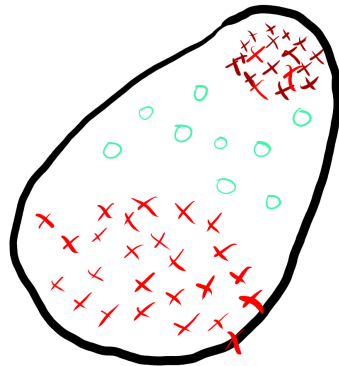
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## Deal with unbalanced data

- Oversample ?



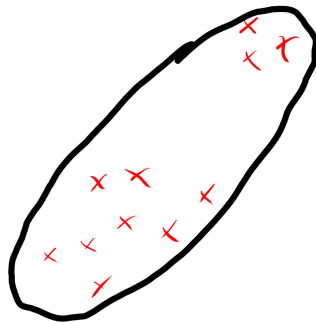
# Deal with unbalanced data

- Oversample ?
- Undersample/saturate ?



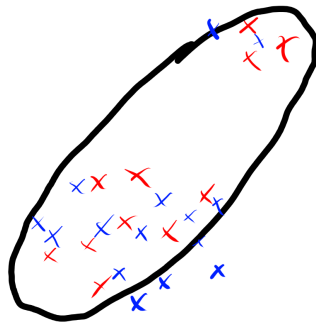
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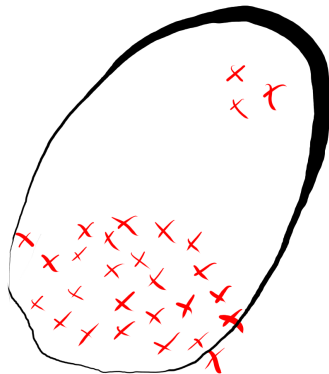
## Deal with unbalanced data

- Oversample ?
- Undersample/saturate ?



## Deal with unbalanced data

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



## Deal with lack of data

- Data augmentation



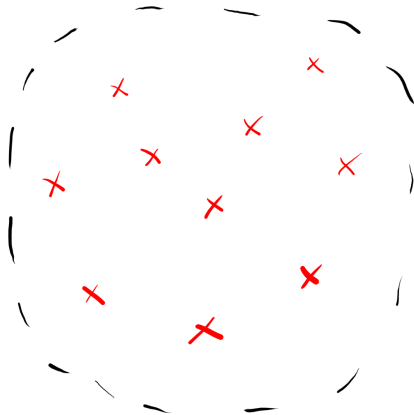
## Deal with lack of data

- Data augmentation



## 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
- Distillation
- Ensembles

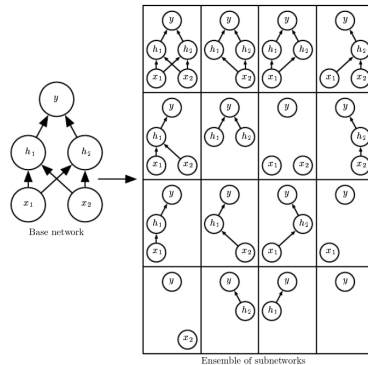


Figure from Goodfellow et al., 2016

**Need to be very careful 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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“random split training validation 80/20”

For the uncurated dataset, we randomly sample 142 million images

Oquab et al., 2023

## Random split ?

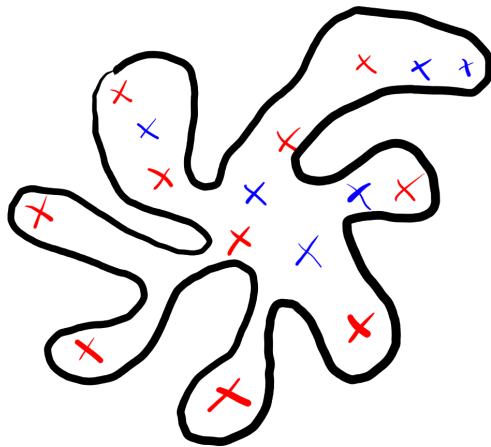
“random split training validation 80/20”

For the uncurated dataset, we randomly sample 142 million images

Oquab et al., 2023

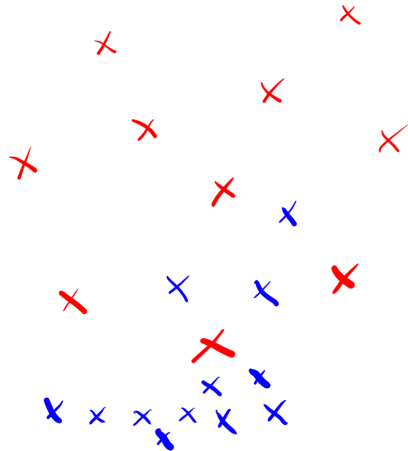
Works for huge DL papers, maybe not for you

## Overfitting the test set

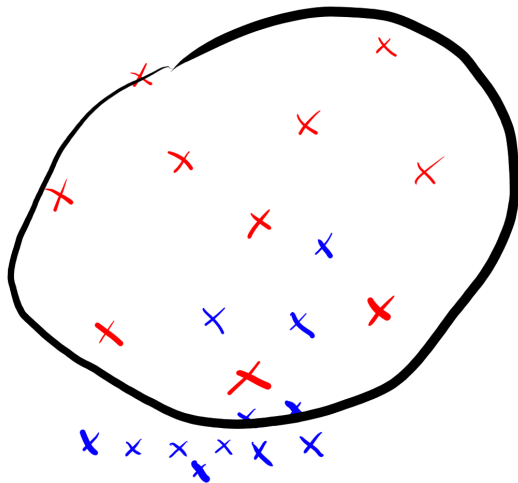




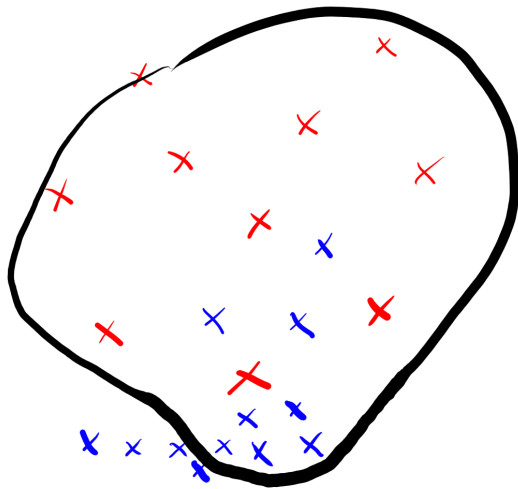
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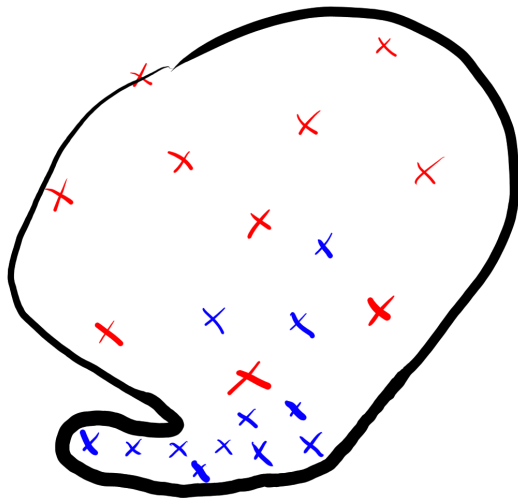
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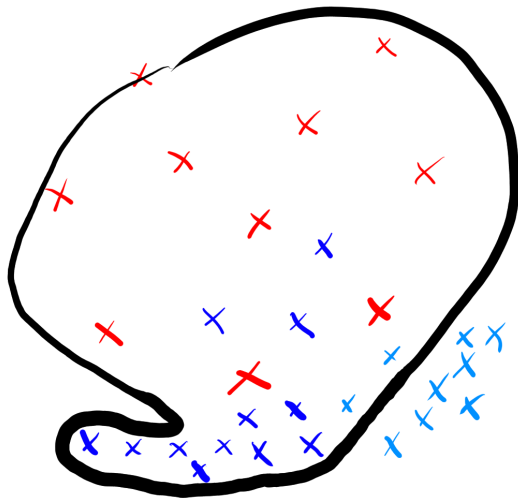
## Overfitting the test set



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# Cross-validation

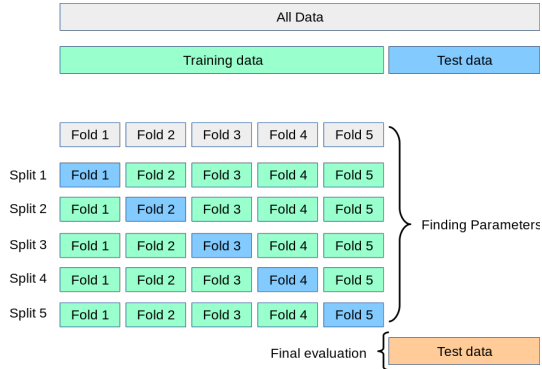


Figure from scikit-learn docs

# Cross-validation

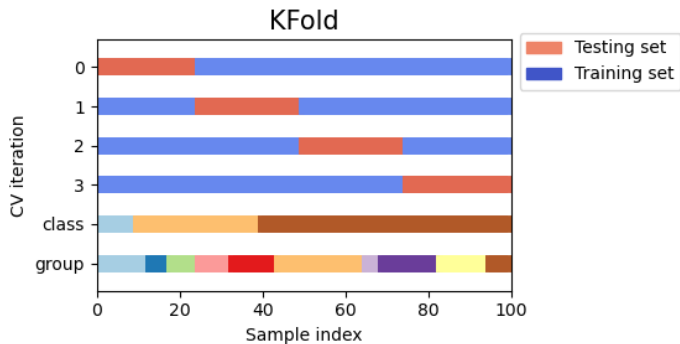


Figure from scikit-learn docs

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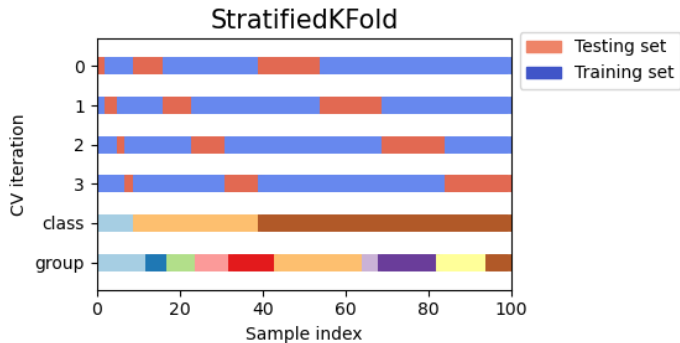


Figure from scikit-learn docs



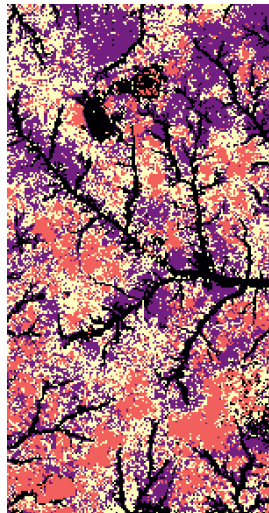
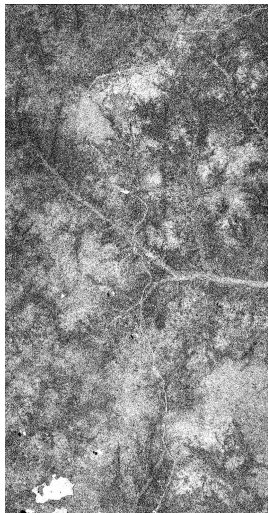
## Case studies

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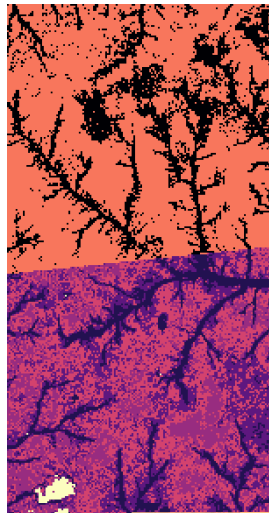
## Case study : Spatial cross-validation



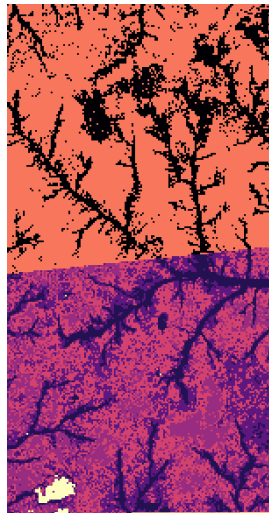
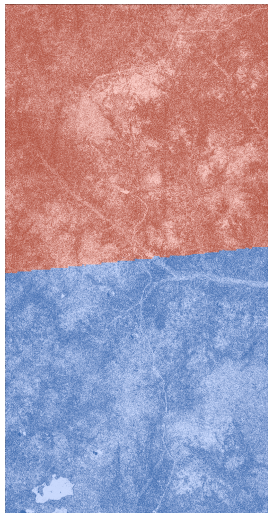
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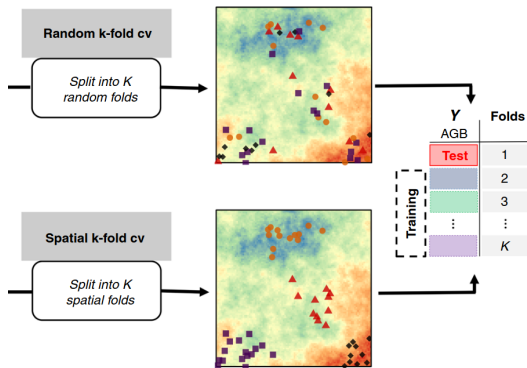
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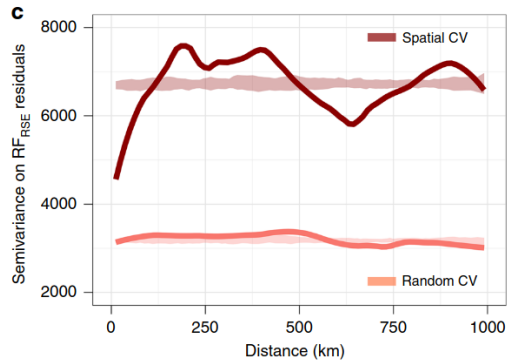


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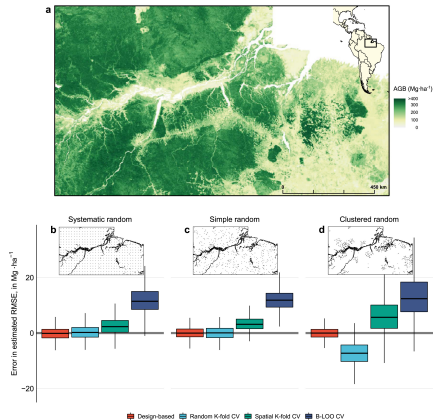
See. Ploton et al., 2020

## Case study : Spatial cross-validation



See. Ploton et al., 2020

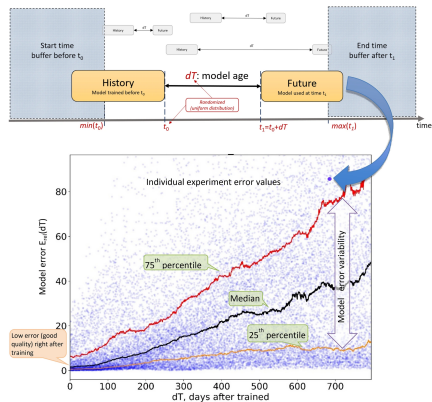
# Case study : Spatial cross-validation



See. Wadoux et al., 2021

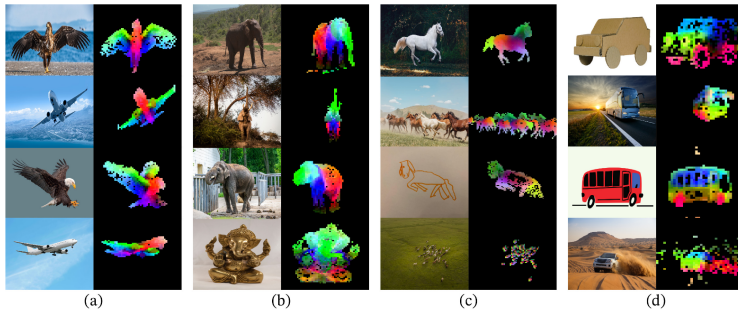


# Case study : Aging models ?



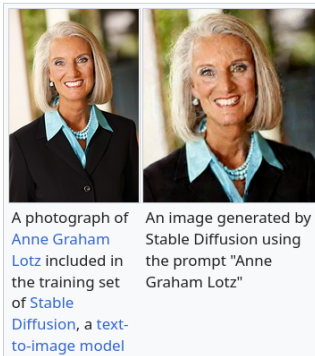
See. Vela et al., 2022

## Perspective : Foundation models ?

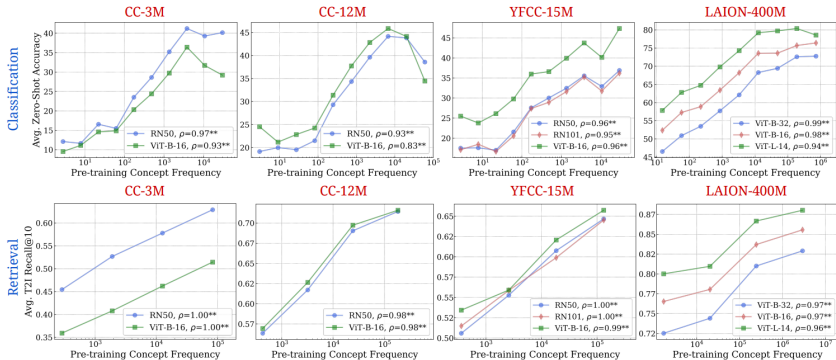


See. Oquab et al., 2023

## Perspective : Foundation models ?



# Perspective : Foundation models ?



See. Udandarao et al., 2024

## Useful 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.
- Udandara, Vishal 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.