

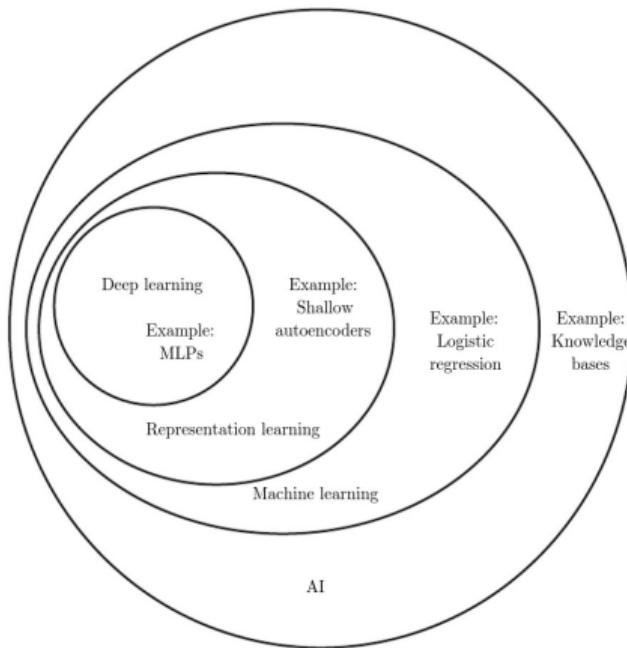
Artificial Intelligence in Ecology and Evolution : potential and limits

E2M2 webinar

Paul Tresson

26/06/25

AI is not only deep learning



Goodfellow et al., 2016

Outline

1. Why use deep learning in ecology ?
2. What are the cases where deep learning does work ?
and other models don't
3. What are the cases where deep learning doesn't work ?
common traps when working with living things
4. How to sample and evaluate ?
5. Perspectives

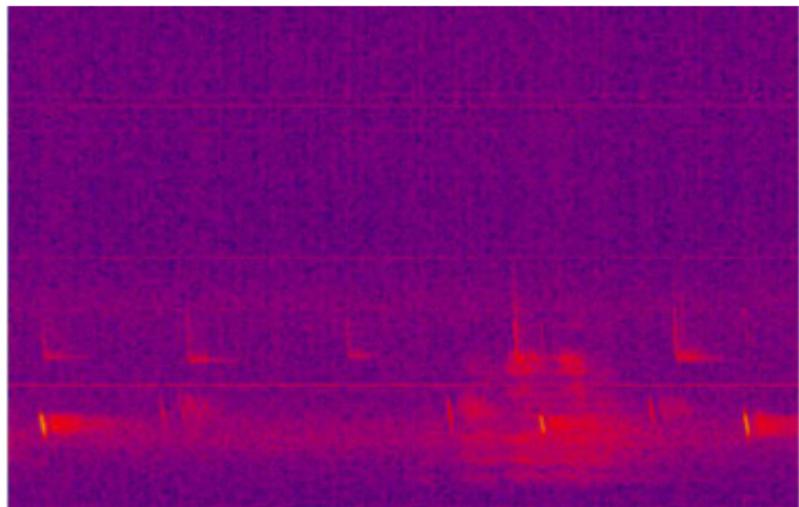
Why use deep learning in ecology ?

More and more data



- UAVs, Satellite

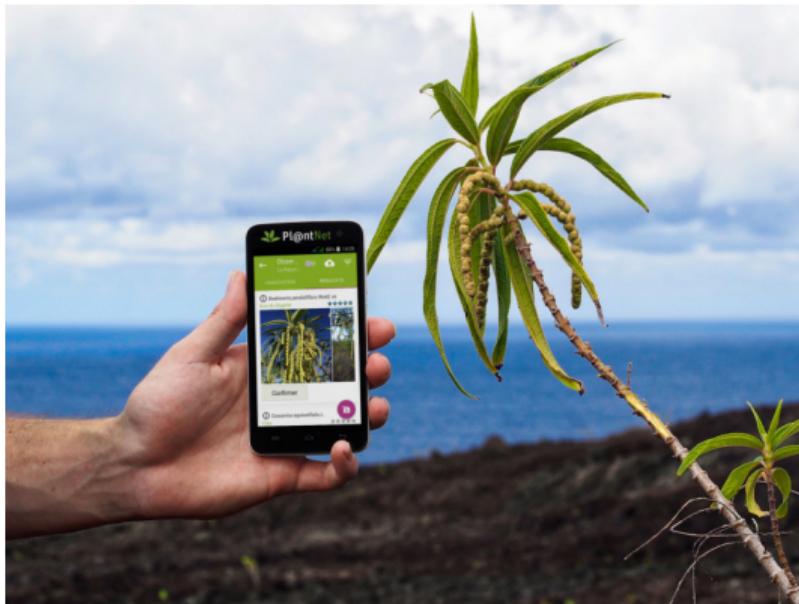
More and more data



- UAVs, Satellite
- Camera trap, acoustic

Mac Aodha *et al.* 2022

More and more data



plantnet.org

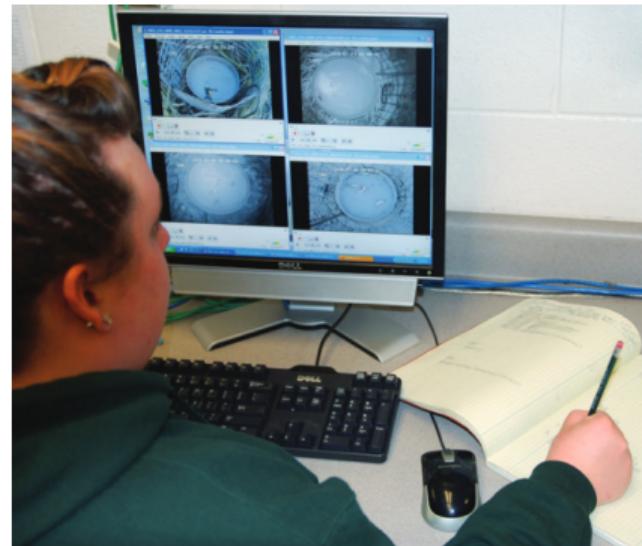
- UAVs, Satellite
- Camera trap, acoustic
- Citizen science

More and more data

- UAVs, Satellite
 - Camera trap, acoustic
 - Citizen science
- **Better coverage, better monitoring**

Data analysis and interpretation is time consuming

- A computer does not sleep
- A computer does not get tired



Grieshop et al., 2012

Data analysis and interpretation is time consuming

- A computer does not sleep
 - A computer does not get tired
- **Automation now possible**



IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.

xkcd 1425, 2014

**What are the cases where deep
learning does work ?**

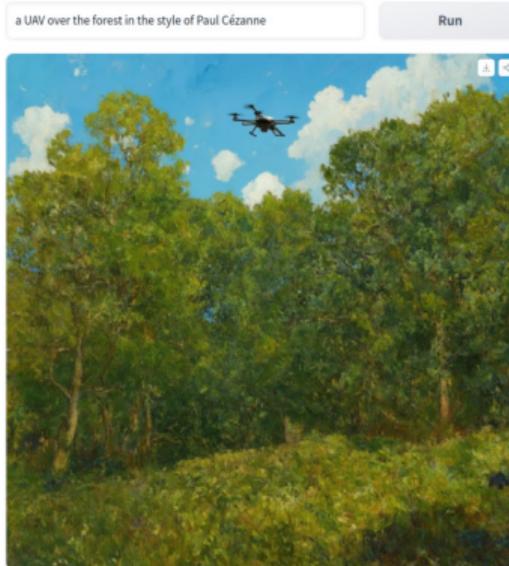
and other models don't

Model complex, non-linear and abstract relationships

Hi can you write me a haiku about forest with a subtle reference to Asterix ?

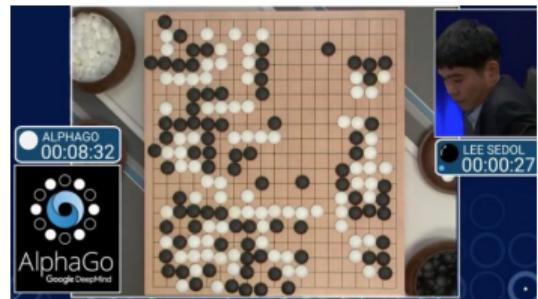
Tall trees whispering,
Mischief stirs in Gaulish woods—
Magic roots run deep.

···



a UAV over the forest in the style of Paul Cézanne

Run



Interpolation and generalisation



Unonopsis stipitata Diels

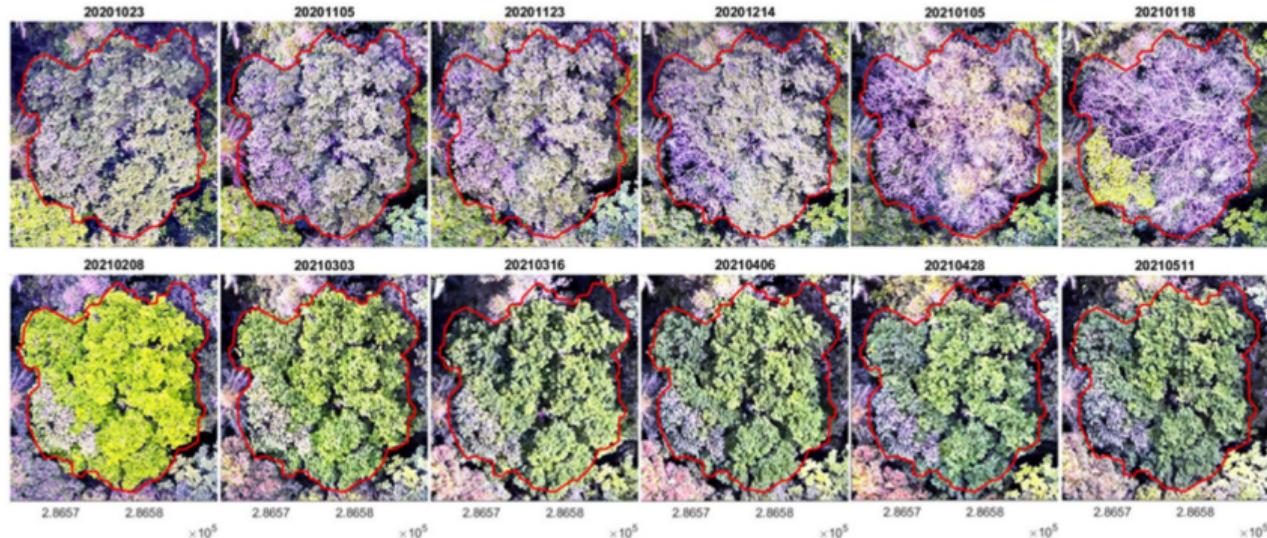
PlantClef 2020 Dataset

What are the cases where deep learning doesn't work ?

common traps when working with living things

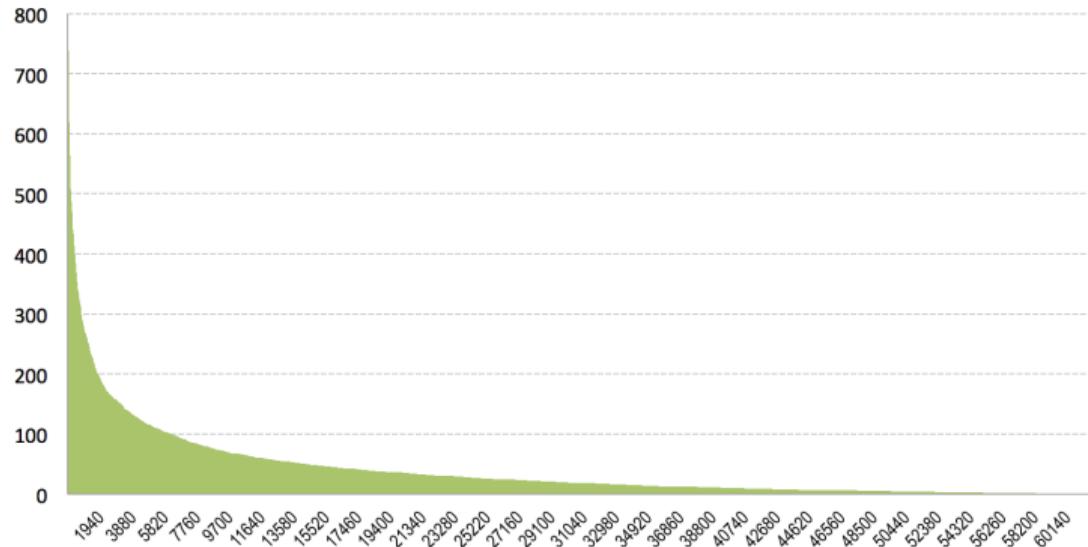
Constraints in ecology

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

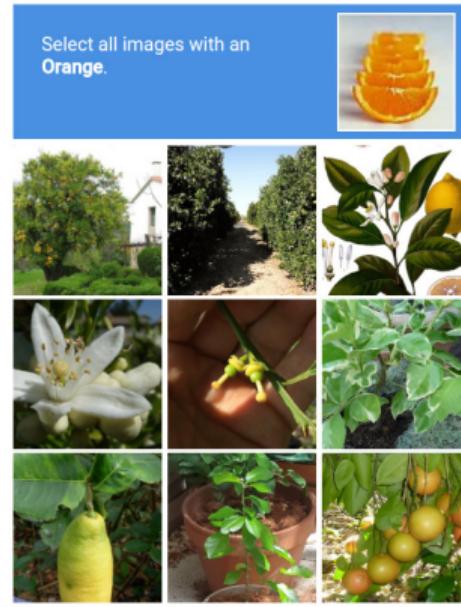
Data from the real world is noisy, unbalanced, hard to collect, hard to interpret.

Select all images with an Orange.

Verify

Constraints in ecology

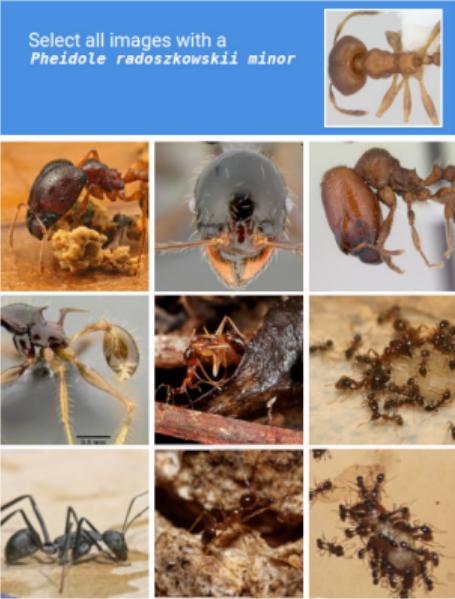
Data from the real world is noisy, unbalanced, hard to collect, hard to interpret.



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



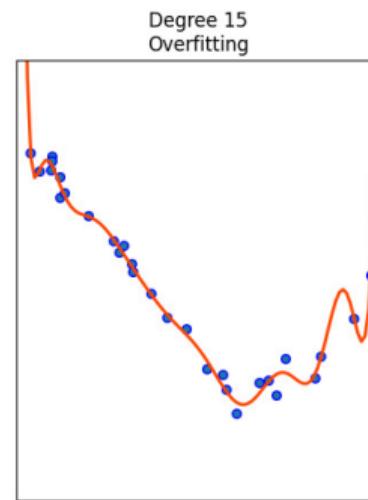
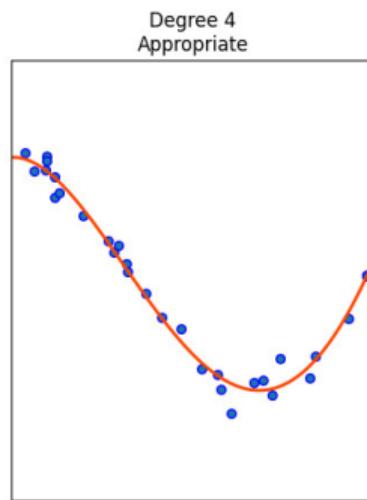
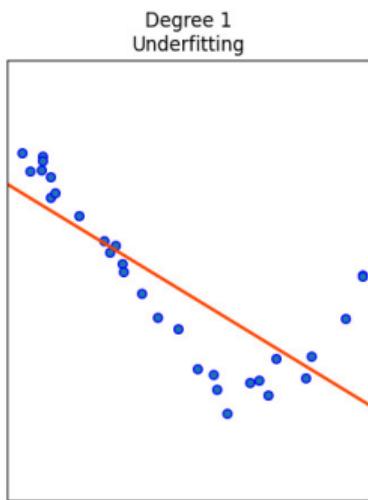
The image shows a 3x3 grid of nine smaller images, each depicting a different ant or group of ants. In the top right corner of the grid, there is a larger, more detailed image of a single ant, which serves as the target for the identification task. The other eight images in the grid show various ants in different contexts, such as close-up views of their heads or bodies, and groups of ants on surfaces like leaves or soil.



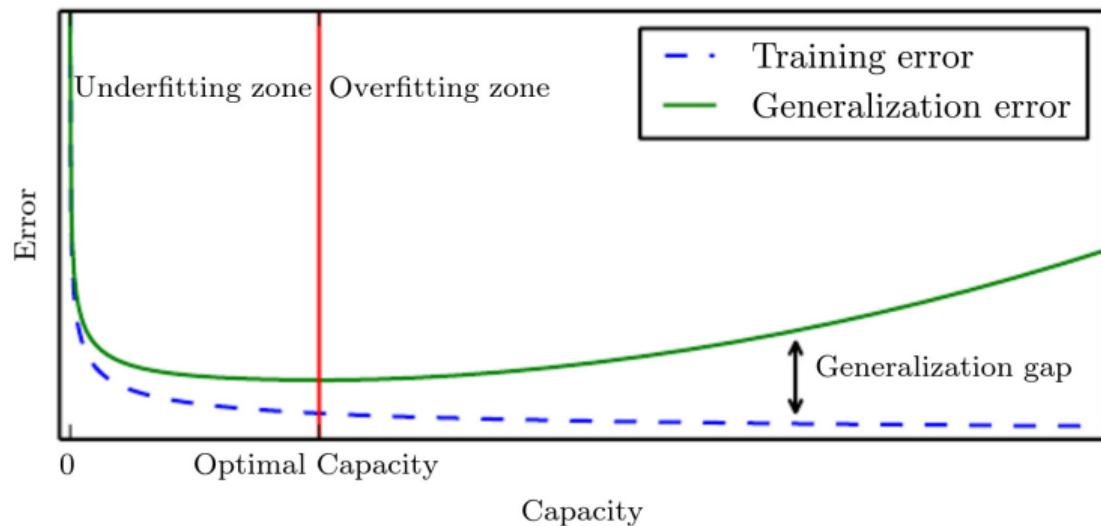
Verify

Overfitting

Overfitting



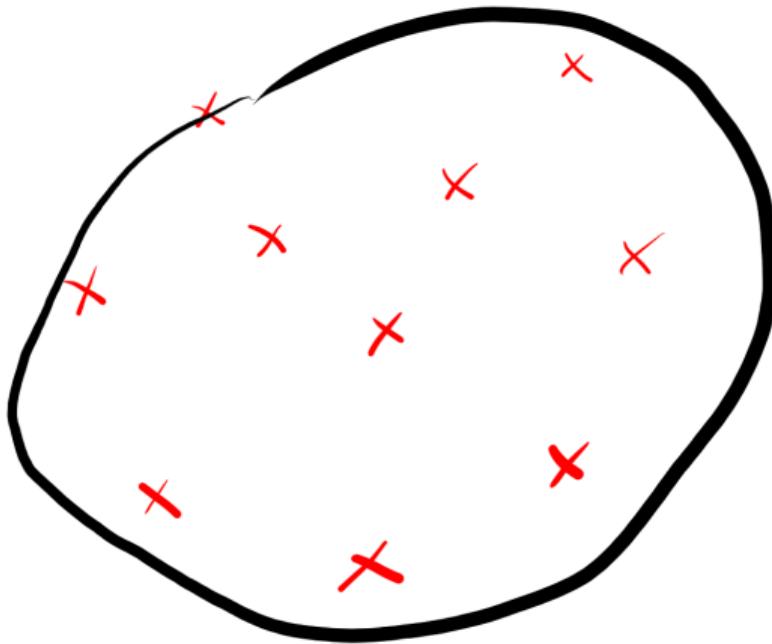
Overfitting



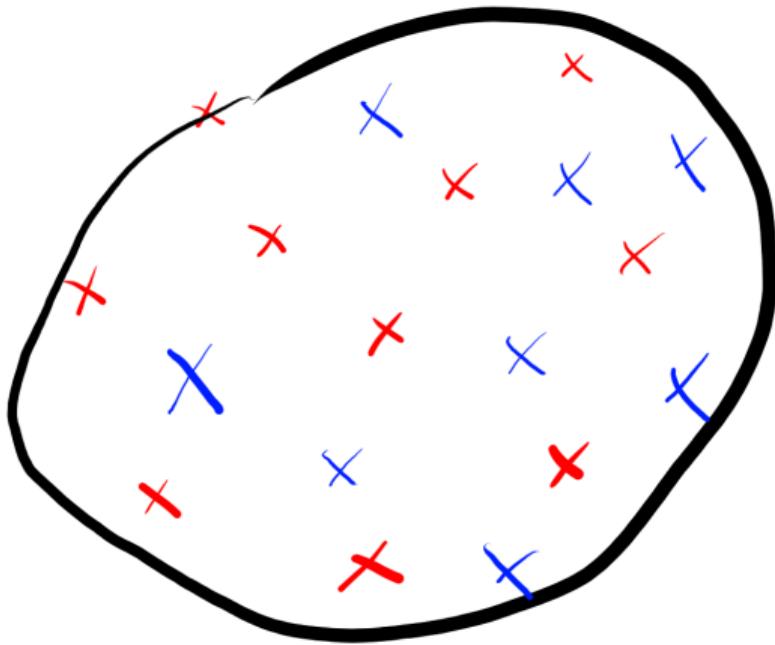
Goodfellow et al., 2016



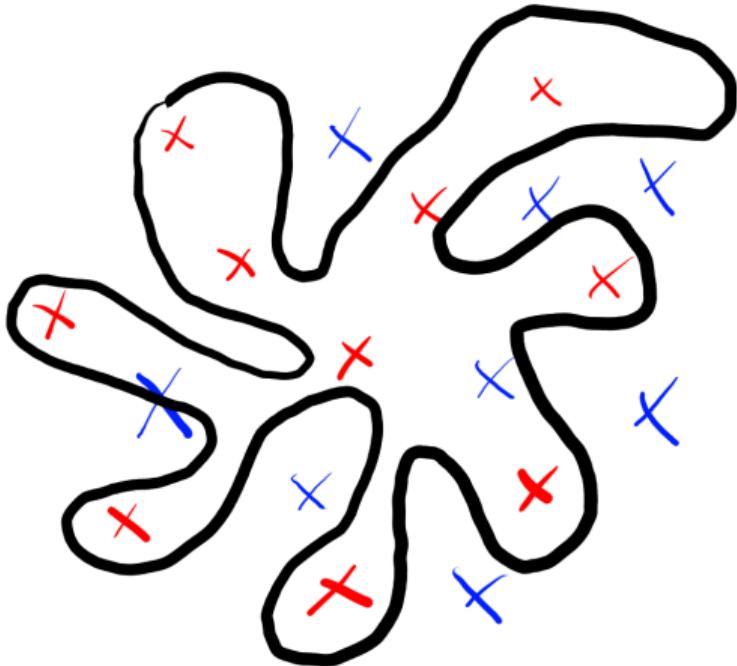
Train set



A good fitted model



Test set



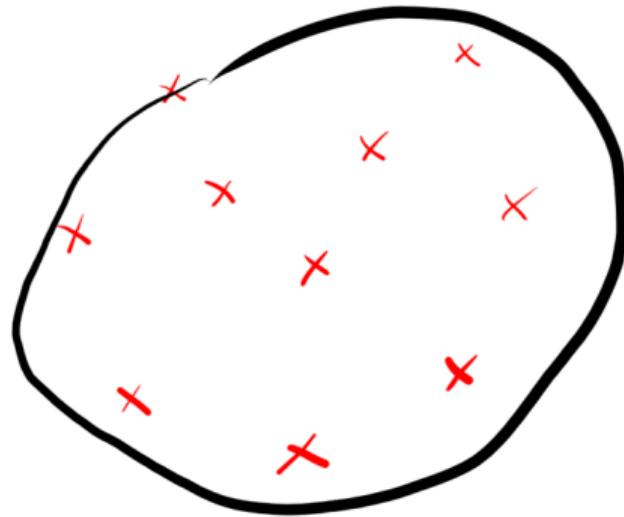
Overfitting

Biases

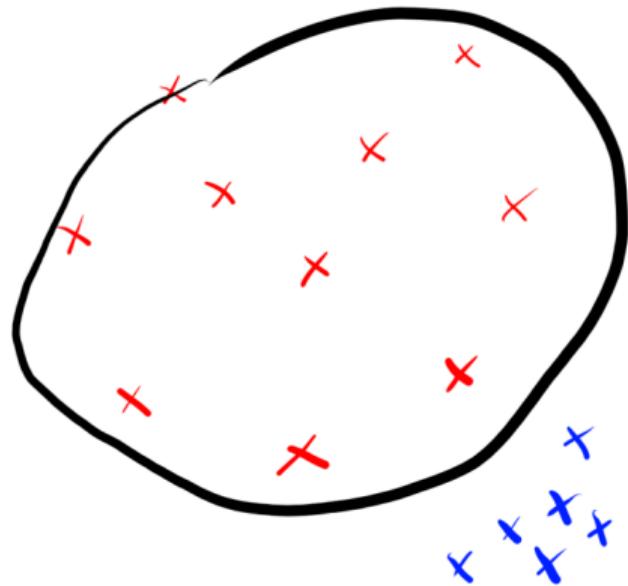
Biases in the train set



Biases in the train set



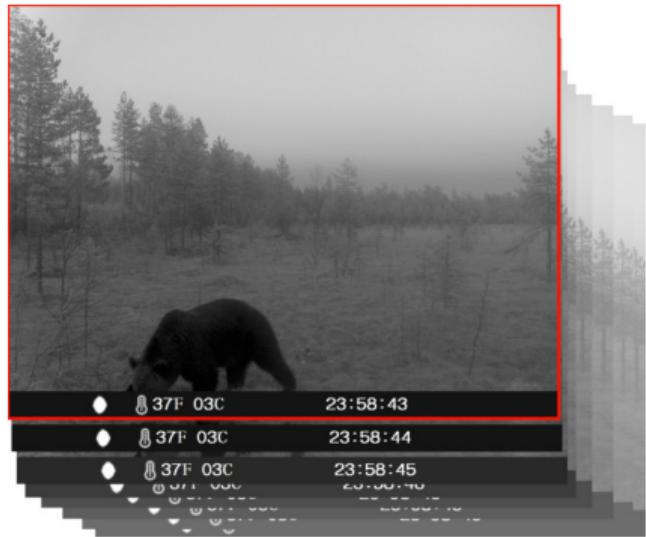
Biases in the train set



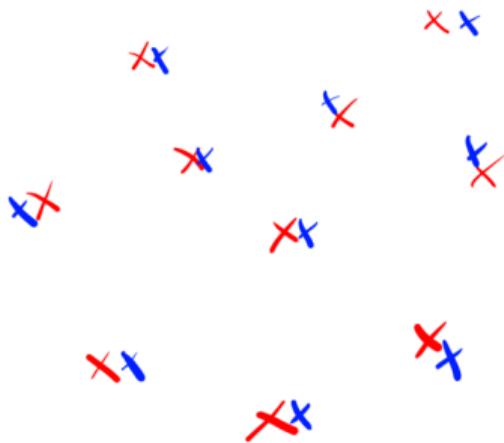
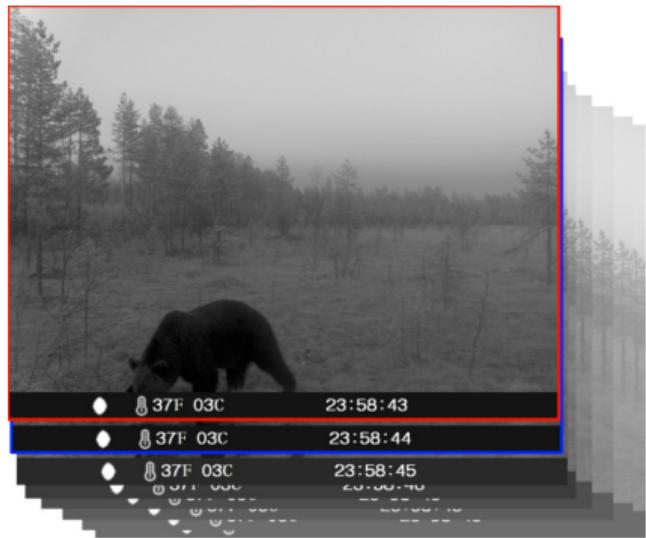
Biases in the train set - autocorrelation



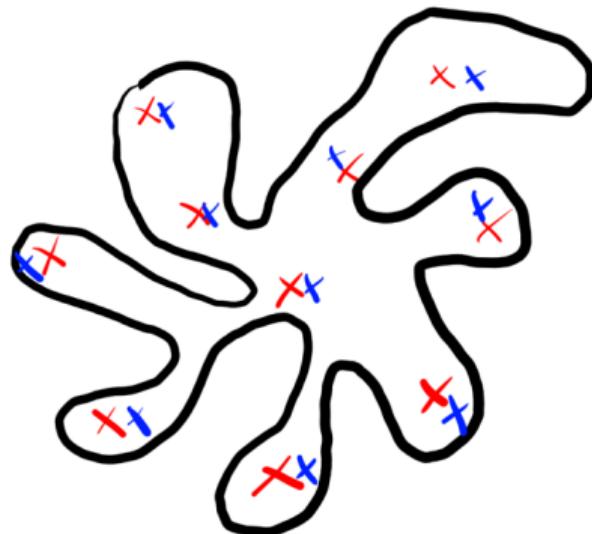
Biases in the train set - autocorrelation



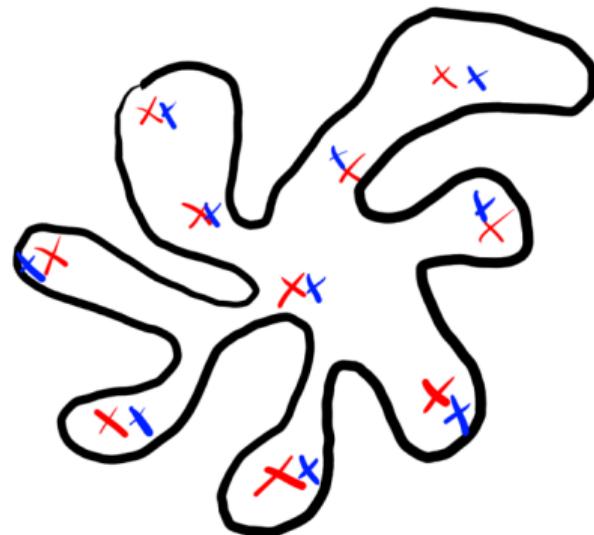
Biases in the train set - autocorrelation



Biases in the train set - autocorrelation



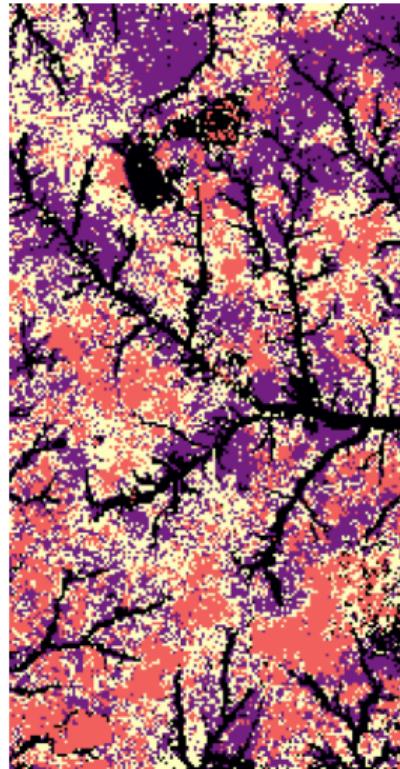
Biases in the train set - autocorrelation



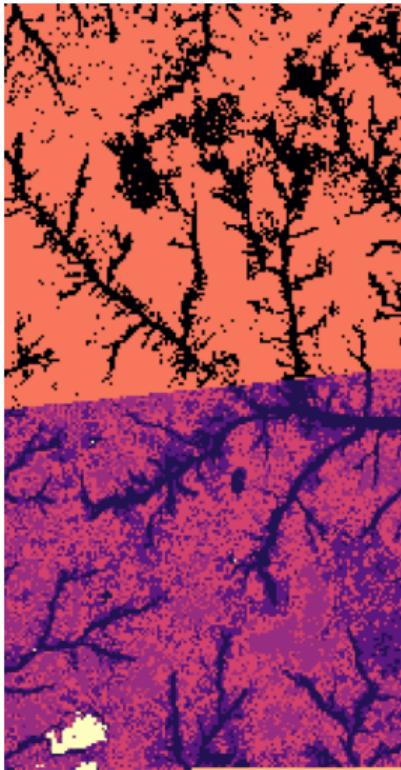
Biases in the train set - Spatial autocorrelation



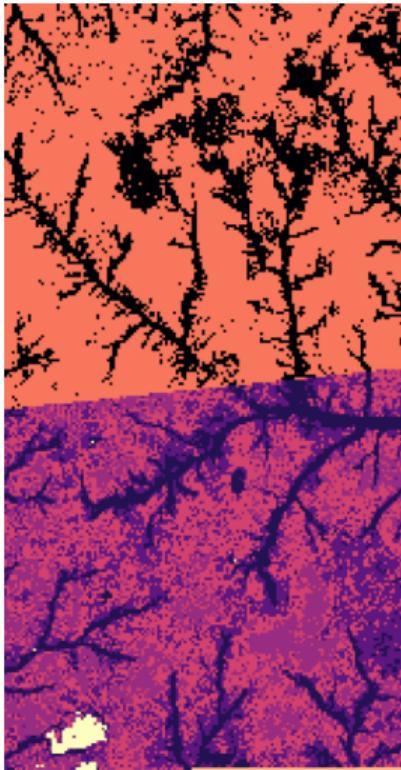
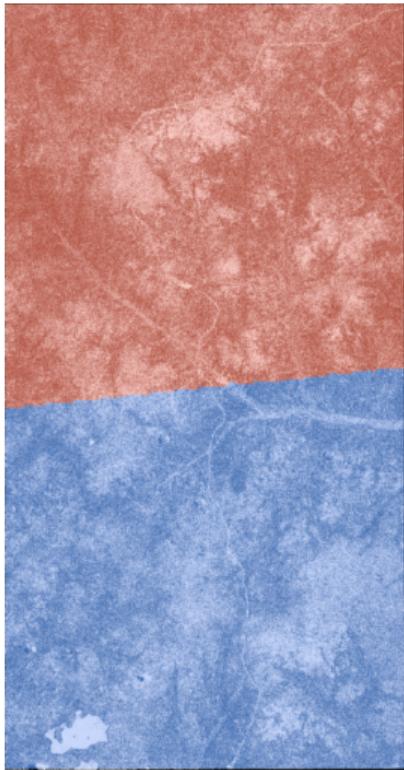
Biases in the train set - Spatial autocorrelation



Biases in the train set - Spatial autocorrelation



Biases in the train set - Spatial autocorrelation



Unbalanced data

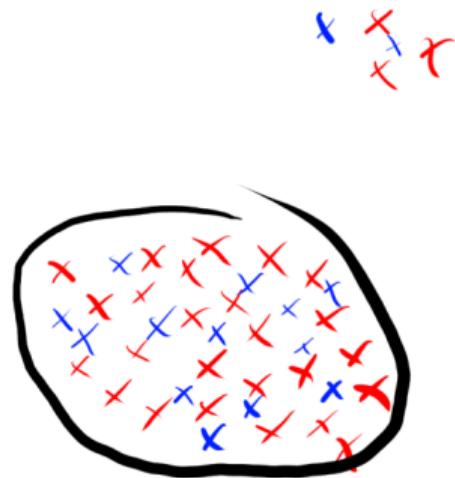
Unbalanced data



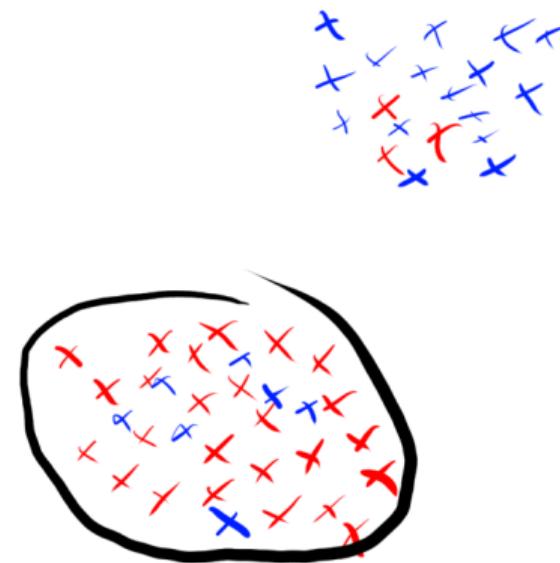
Unbalanced data



Unbalanced data



Unbalanced data



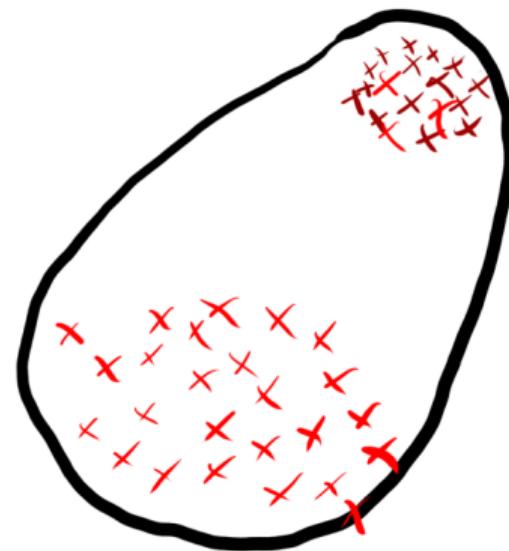
Deal with unbalanced data

- Oversample ?



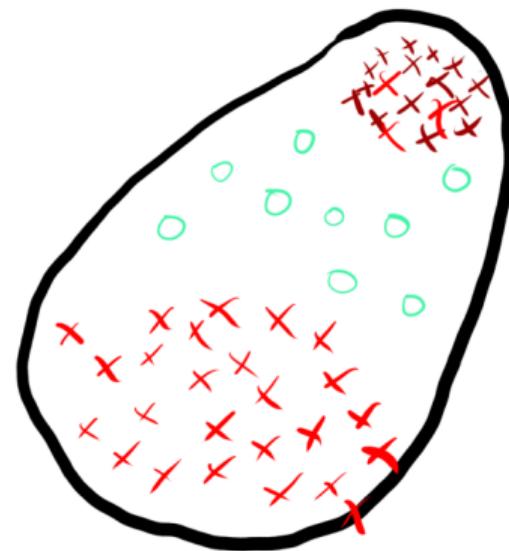
Deal with unbalanced data

- Oversample ?



Deal with unbalanced data

- Oversample ?



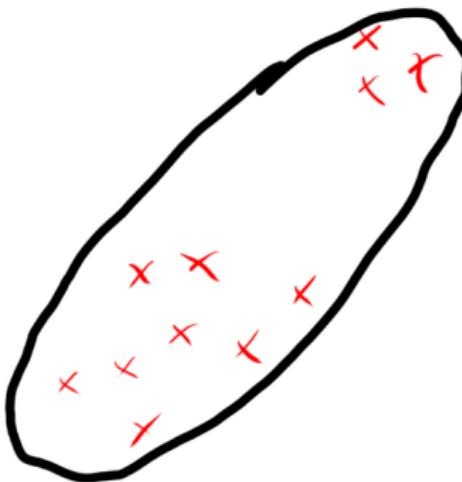
Deal with unbalanced data

- Oversample ?
- Undersample/saturate ?



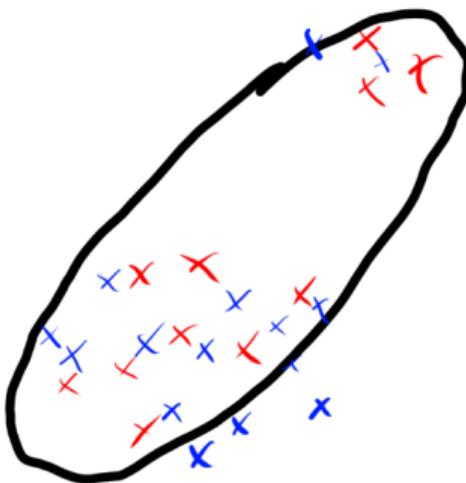
Deal with unbalanced data

- Oversample ?
- Undersample/saturate ?



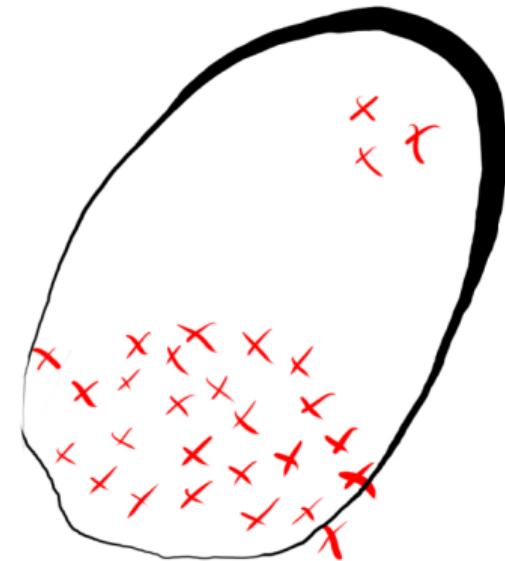
Deal with unbalanced data

- Oversample ?
- Undersample/saturate ?



Deal with unbalanced data

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



Deal with lack of data

- Data augmentation



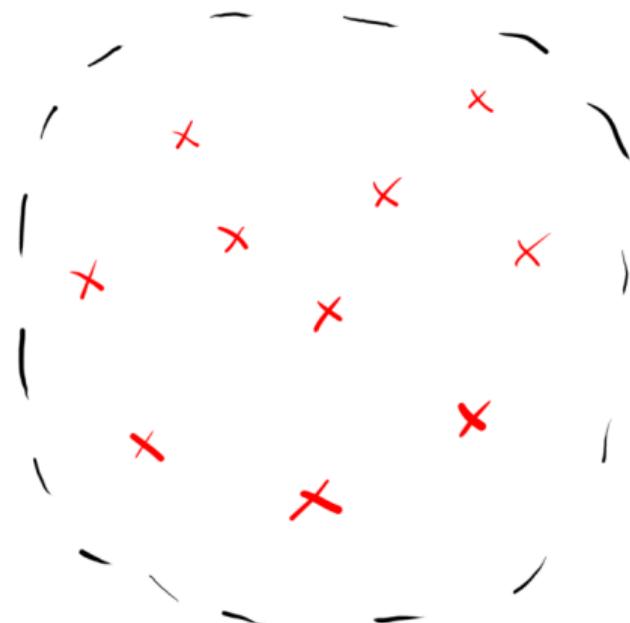
Deal with lack of data

- Data augmentation



Deal with lack of data

- Data augmentation
- Pretrained model

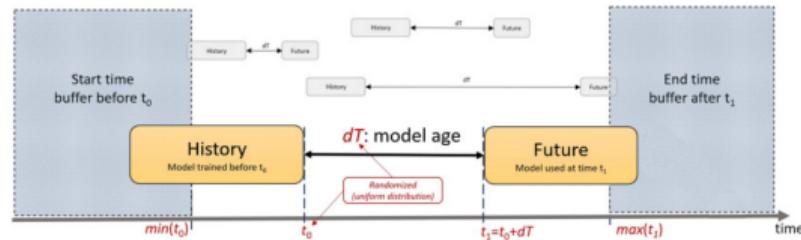


Deal with lack of data

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

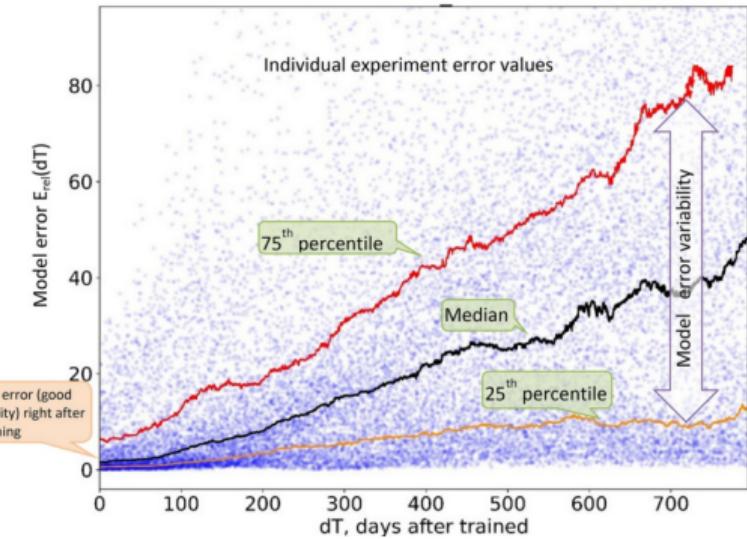
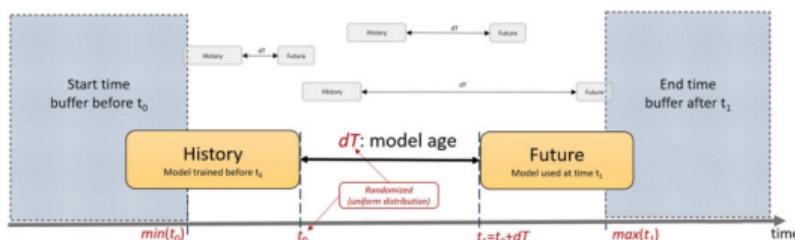
Out of distribution

Out of distribution : Evolution with time



Adapted from Vela et al., 2022

Out of distribution : Evolution with time



Adapted from Vela et al., 2022

Out of distribution : Global changes

Conditions will evolve in never seen before conditions:

- Given ecosystem in unprecedented climatic conditions

Out of distribution : Global changes

Conditions will evolve in never seen before conditions:

- Given ecosystem in unprecedented climatic conditions
- Species migrate/invoke in new territories

Out of distribution : Invasive species

New unknown species in the training test appears in a region.

- False Positive : confusion with known species

Out of distribution : Invasive species

New unknown species in the training test appears in a region.

- False Positive : confusion with known species
- False Negative : model misses the new species

Out of distribution : Invasive species

New unknown species in the training test appears in a region.

- False Positive : confusion with known species
- False Negative : model misses the new species
- Handmade check on model confidence

Need to be very careful on how to evaluate

How to sample and evaluate ?

Random split ?

“random split training validation 80/20”

Random split ?

“random split training validation 80/20”

For the uncurated dataset, we randomly sample 142 million images

Oquab et al., 2023

Random split ?

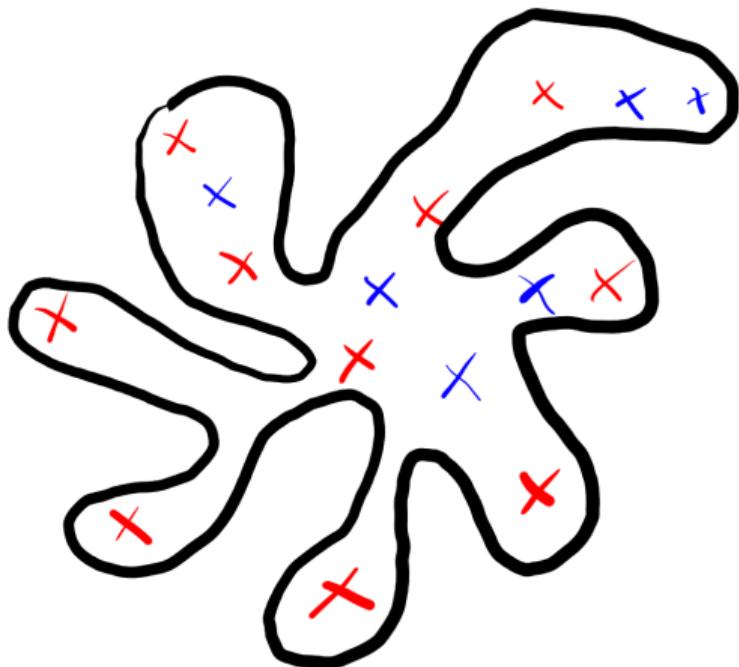
“random split training validation 80/20”

For the uncurated dataset, we randomly sample 142 million images

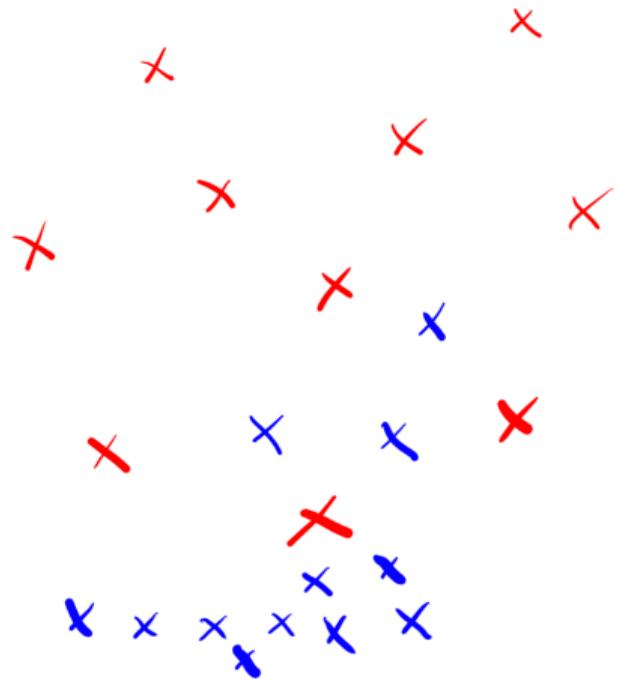
Oquab et al., 2023

Works for huge DL papers, maybe not for you

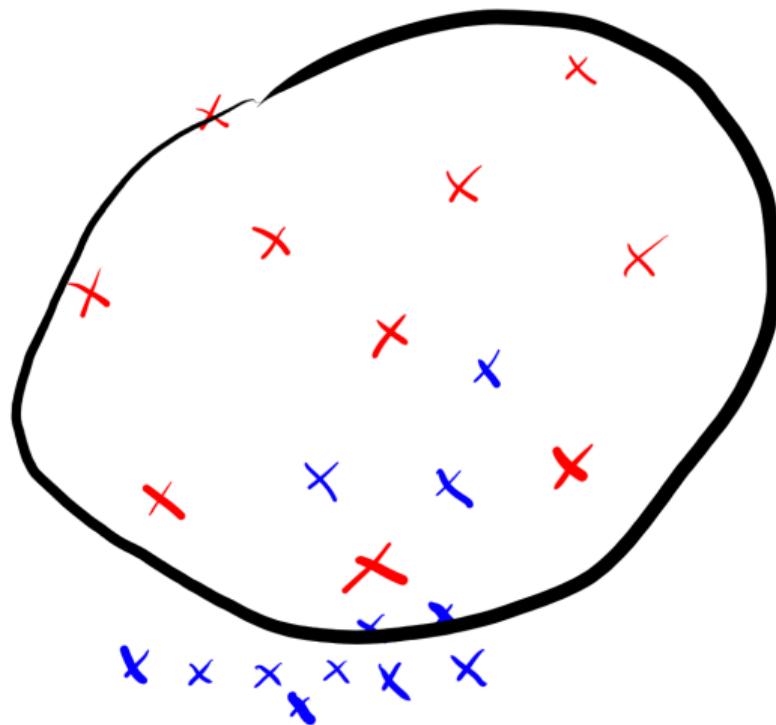
Overfitting the test set



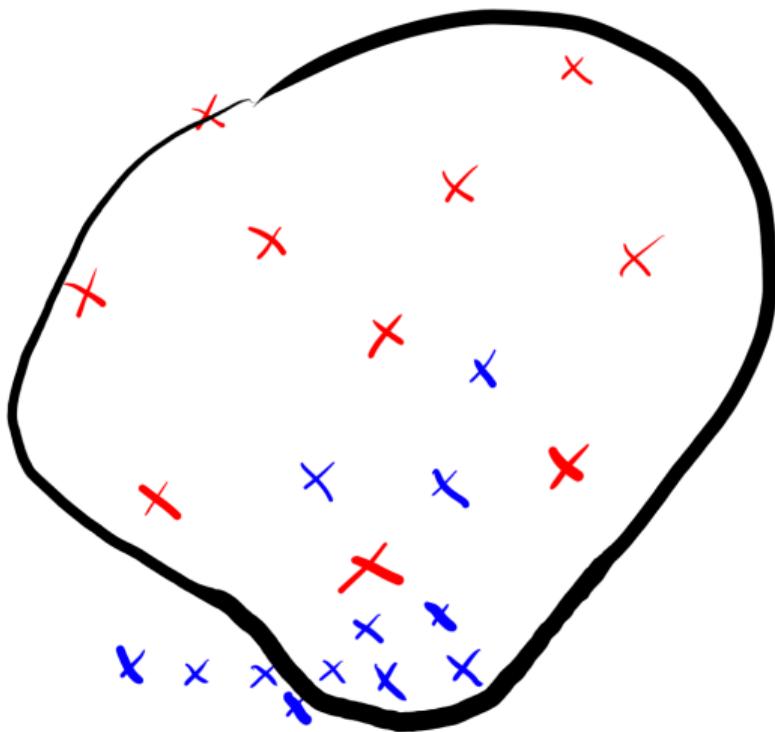
Overfitting the test set



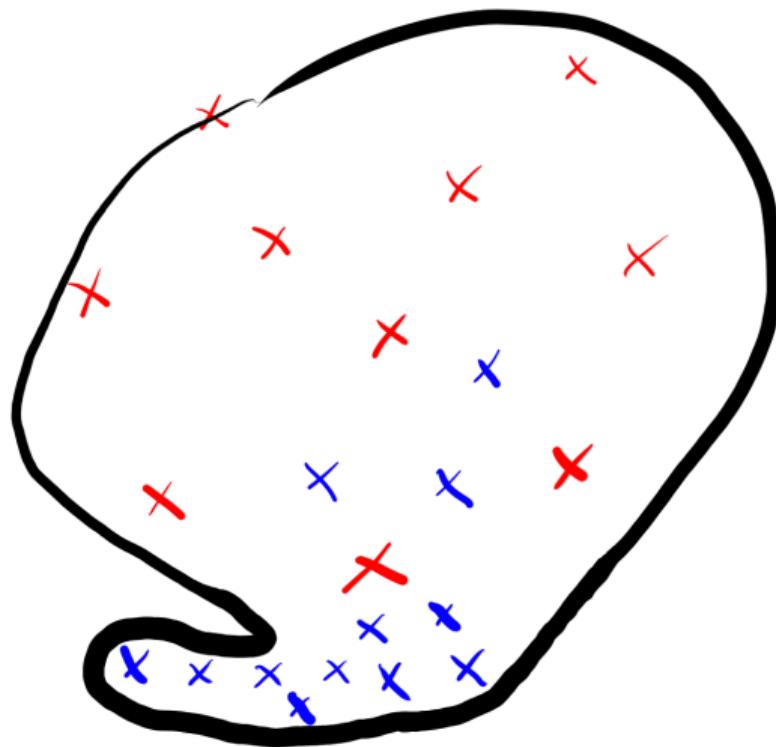
Overfitting the test set



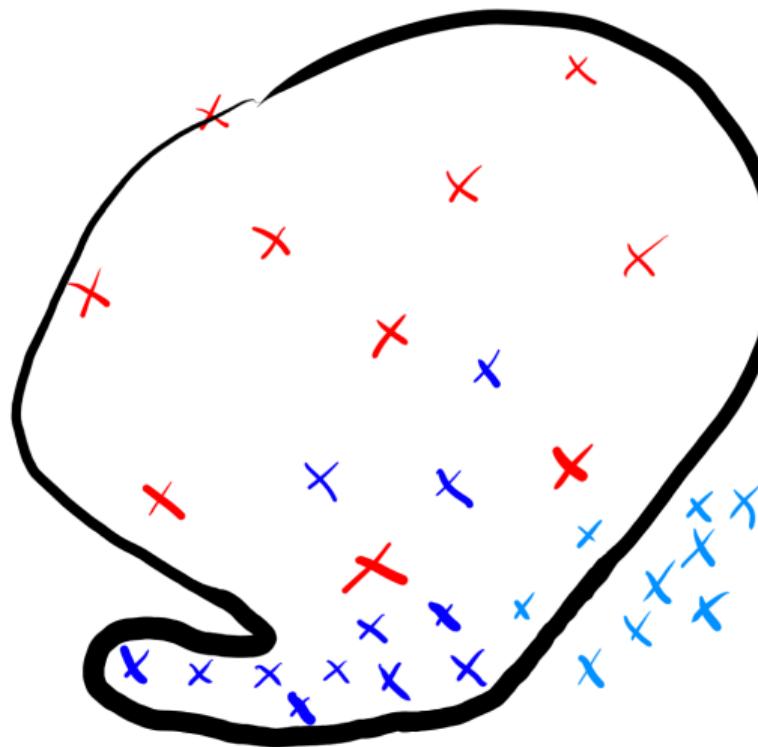
Overfitting the test set



Overfitting the test set



Overfitting the test set



Cross-validation

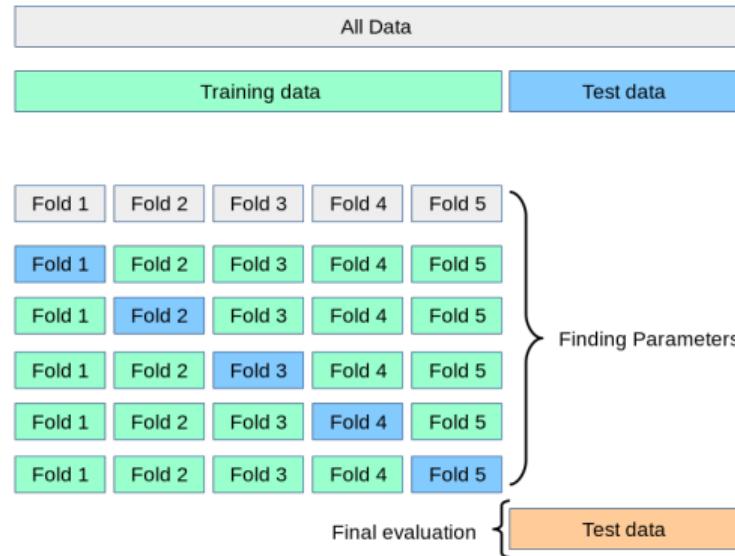


Figure from scikit-learn docs

Cross-validation

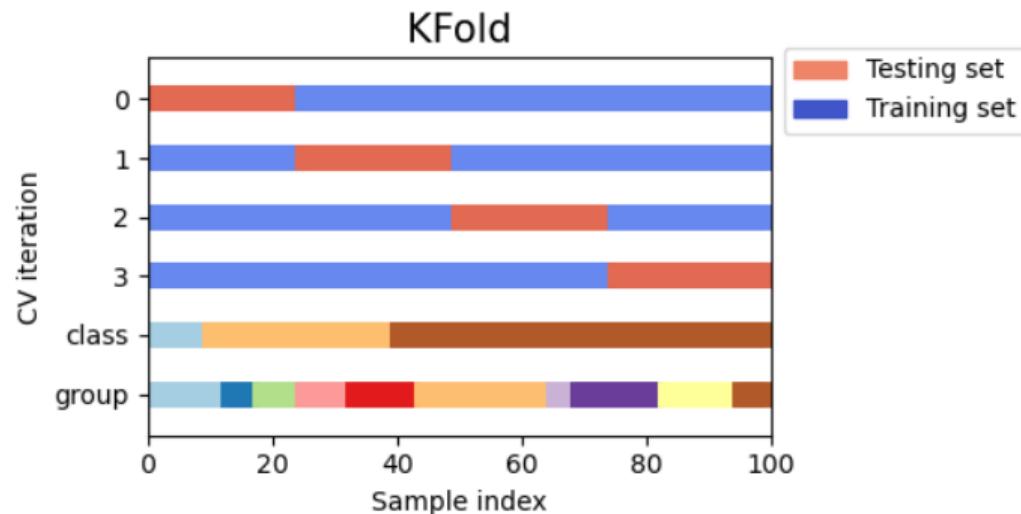


Figure from scikit-learn docs

Cross-validation

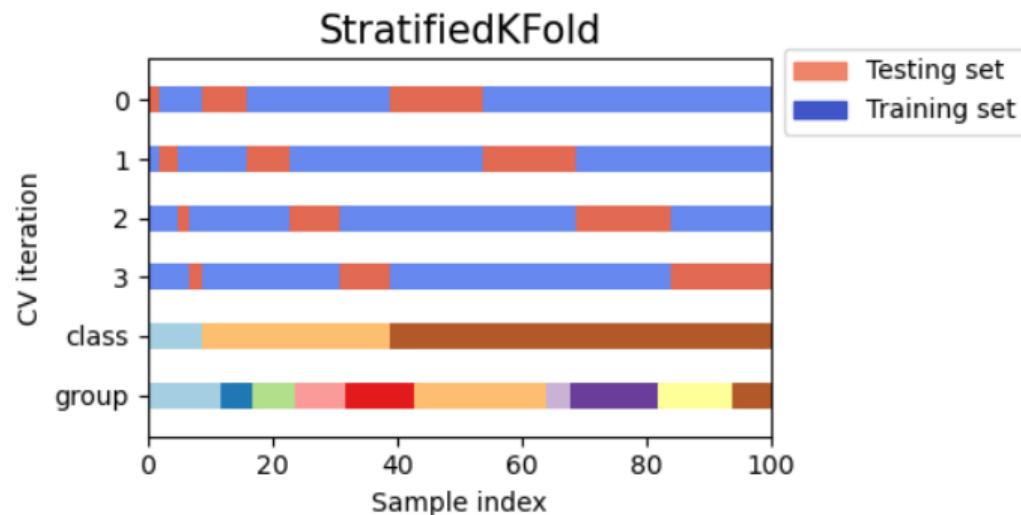
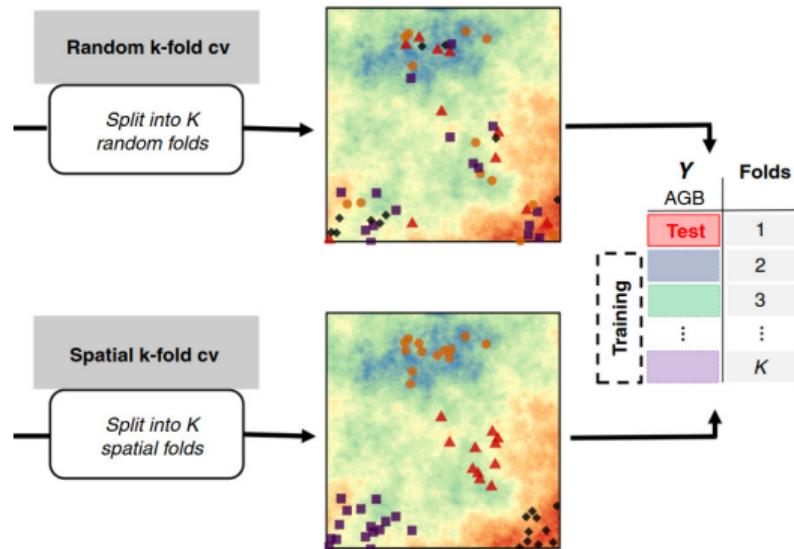


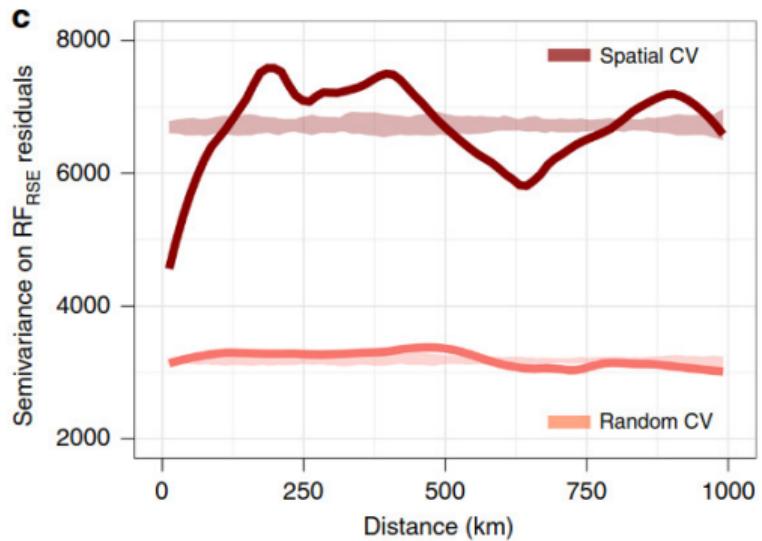
Figure from scikit-learn docs

Spatial cross-validation



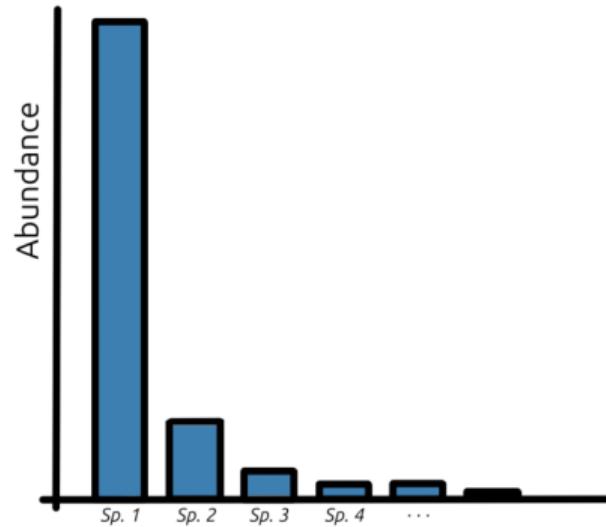
See. Ploton et al., 2020

Spatial cross-validation

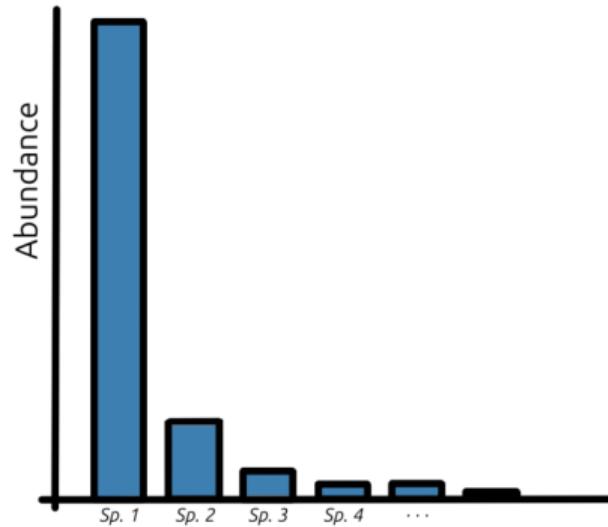


See. Ploton et al., 2020

Choosing the right metric



Choosing the right metric



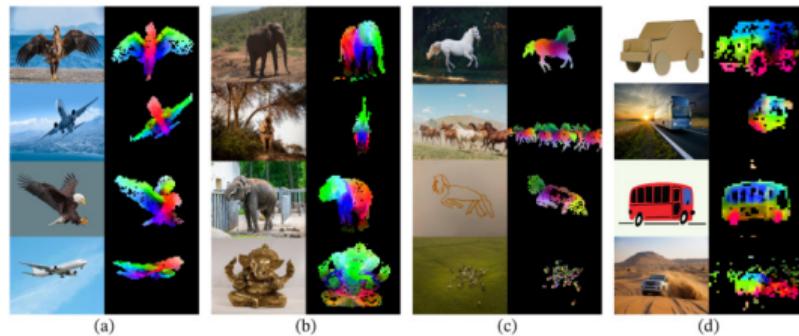
If we predict Sp. 1 all the time:

Accuracy = 0.75

Average precision = 0.05

Perspectives

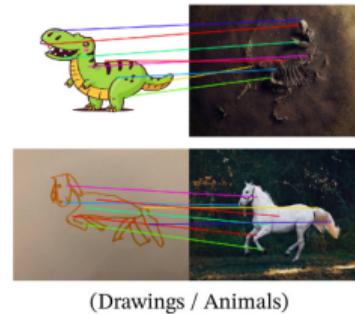
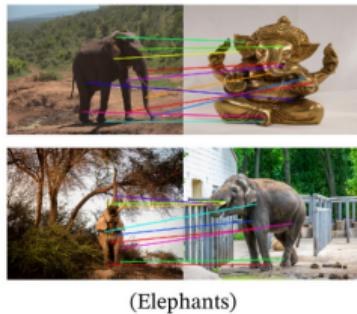
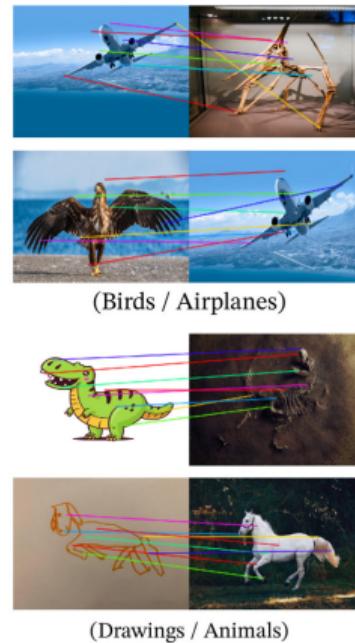
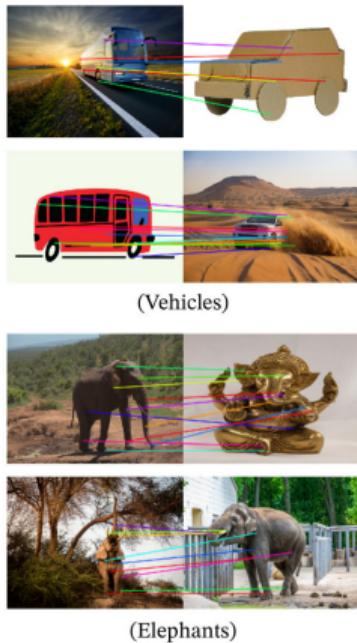
Models are more robust and generalist



- Self-supervised Learning (Pre-training)

Oquab et al., 2023

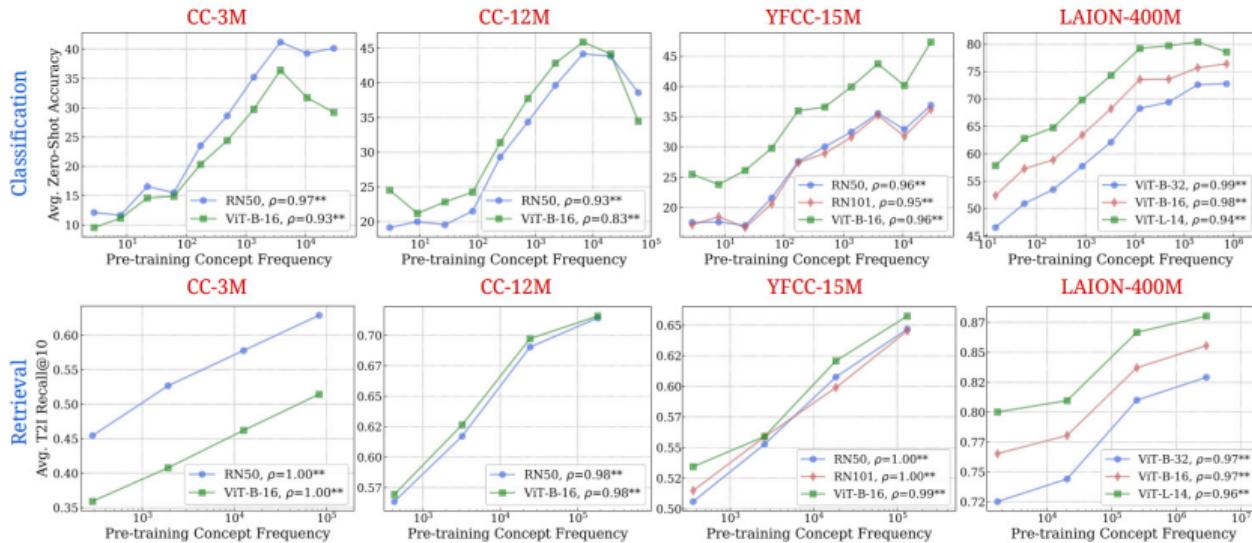
Models are more robust and generalist



- Self-supervised Learning (Pre-training)
- Better performances and robustness

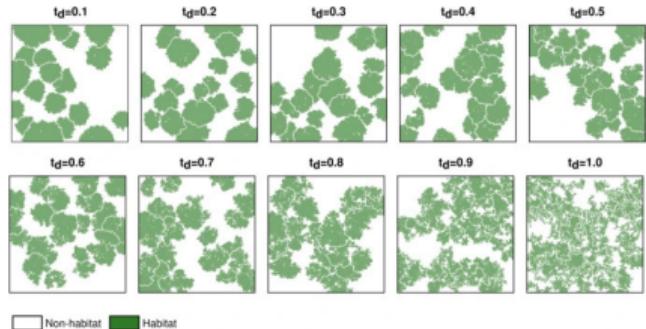
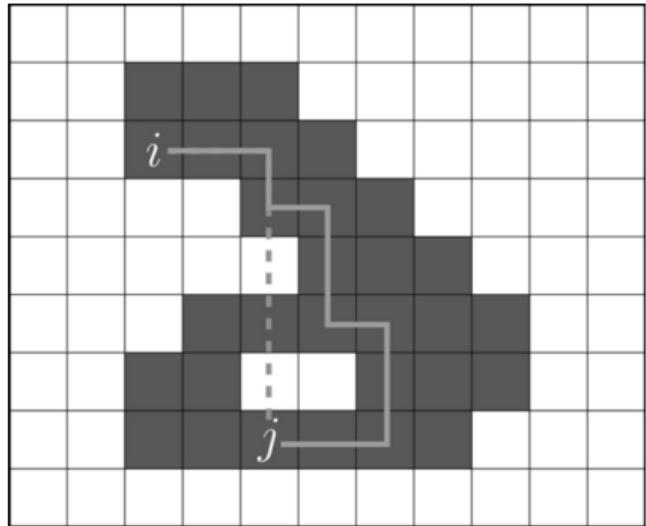
Oquab et al., 2023

Zero-shot at a cost



Udandarao et al., 2024

Not only deep learning



Justeau-Allaire et al., 2024

Conclusion

Should I use deep learning in my research ?

- ✓ Lot of incoming data ✗ Need for explainability
- ✓ Low-level data ✗ Need for certainty
- ✓ Cumbersome but (relatively) easy to analyse ✗ Need for reliability

Thank you for your attention !

Any questions?

Useful ressources

State of the art

- Huggingface
- PapersWithCode

Getting started

- Pytorch
- Keras

Understanding papers

- Yannic Kilcher
- AI coffe break

Understanding visually

- 3blue1brown
- deepia

References i

- Goodfellow, Ian, Yoshua Bengio, Aaron Courville, and Yoshua Bengio (2016). **Deep learning**. Vol. 1. 2. MIT press Cambridge.
- Grieshop, Matthew J et al. (2012). “**Big brother is watching: studying insect predation in the age of digital surveillance**”. In: *American Entomologist* 58.3, pp. 172–182.
- Justeau-Allaire, Dimitri et al. (2024). “**Refining intra-patch connectivity measures in landscape fragmentation and connectivity indices**”. In: *Landscape Ecology* 39.2, p. 24.
- Oquab, Maxime et al. (2023). “**Dinov2: Learning robust visual features without supervision**”. In: *arXiv preprint arXiv:2304.07193*.

References ii

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