Artificial Intelligence in Ecology and Evolution : potential and limits

E2M2 webinar

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26/06/25

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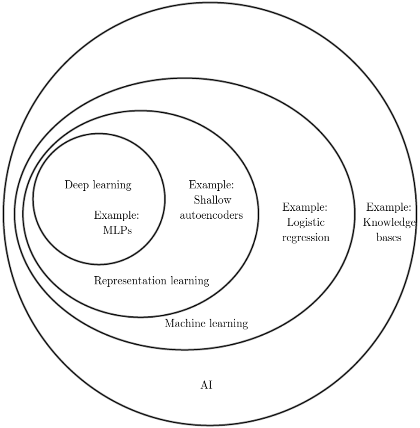
Disclaimer

AI is not just deep learning



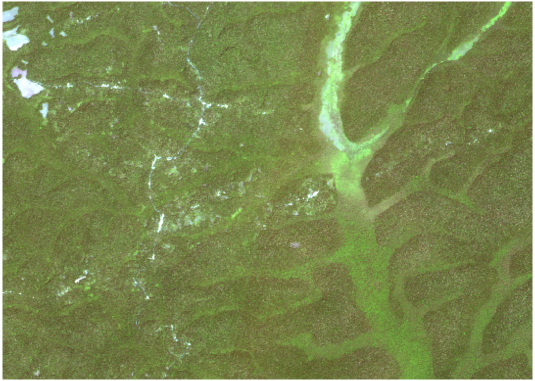
Goodfellow et al., 2016

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

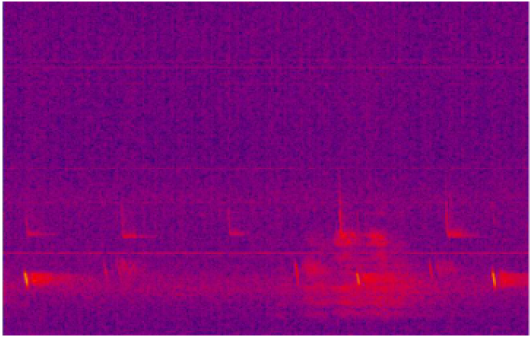
Why use deep learning in ecology ?

More and more data



- UAVs, Satellite

More and more data



- UAVs, Satellite
- Camera trap, accoustic

Mac Aodha *et al.* 2022

More and more data

plantnet.org

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

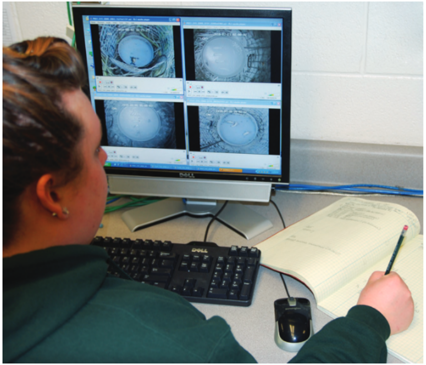
More and more data

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

➔ **Better coverage, better monitoring**

Data analysis and interpretation is time consuming

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

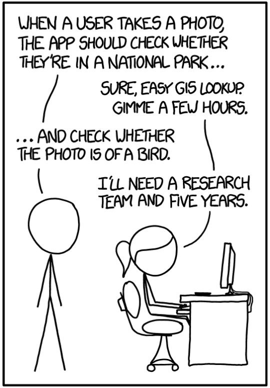


Grieshop et al., 2012

Data analysis and interpretation is time consuming

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

➔ **Automation now possible**



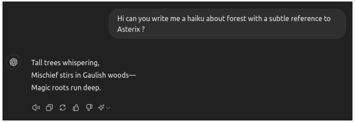
IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.

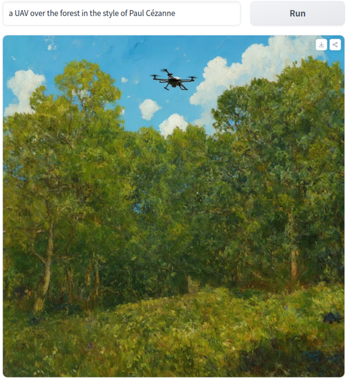
xkcd 1425, 2014

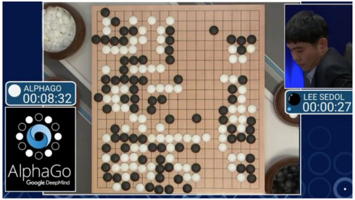
What are the cases where deep learning does work ?

and other models don’t

Model complex, non-linear and abstract relationships







Interpolation and generalisation

Unonopsis stipitata Diels

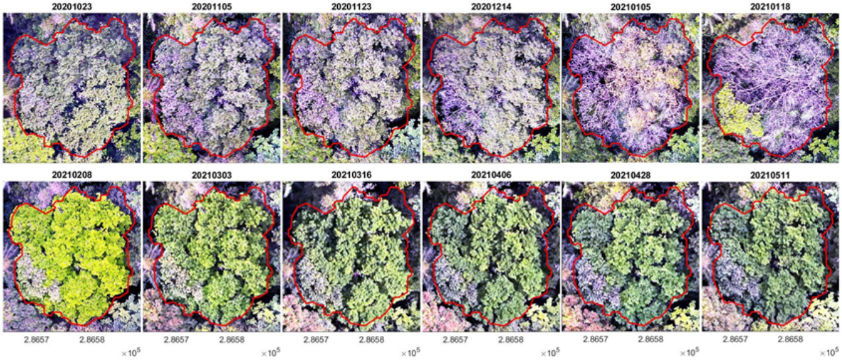
PlantClef 2020 Dataset

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

common traps when working with living things

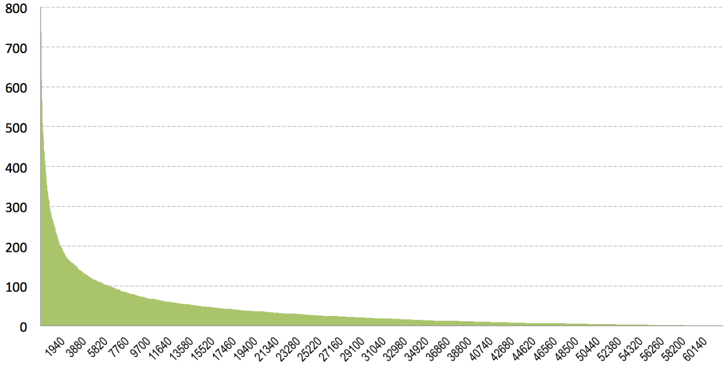
Contraints in ecology

Data from the real world is noisy,



Contraints in ecology

Data from the real world is noisy, unbalanced,

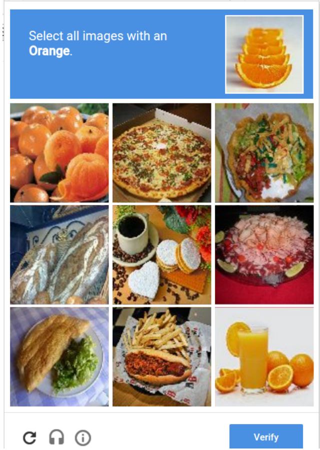


Contraints in ecology

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

Contraints in ecology

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



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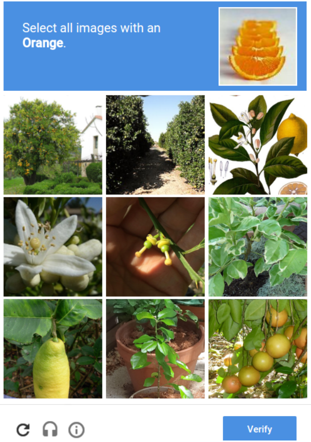


Contraints in ecology

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

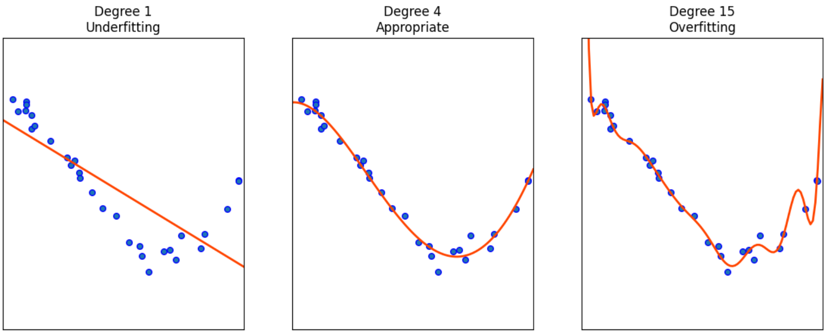
➔ smaller datasets than in most deep learning

We argue that a dataset can be considered large (not small) when the dataset consists of > 100,000 annotated samples, or when it covers the entire probability distribution in a high-dimensional space. For example, there are several free large datasets that can be used for DL: the ImageNet dataset, containing over 14 million annotated images (Russakovsky et al., 2015), the Common Objects in Context (COCO) dataset, containing 330 K images, 1.5 million object instances, and 80 object categories (Lin et al., 2015), and the OpenImages dataset, containing over 9 million images (Kuznetsova et al., 2020). These datasets can be

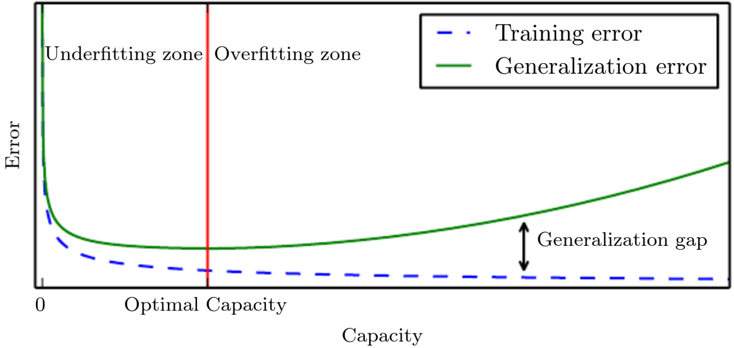
Safonova et al., 2023

Overfitting

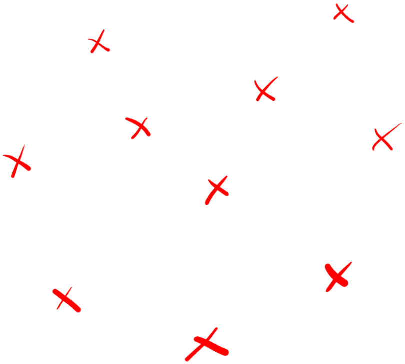
Overfitting



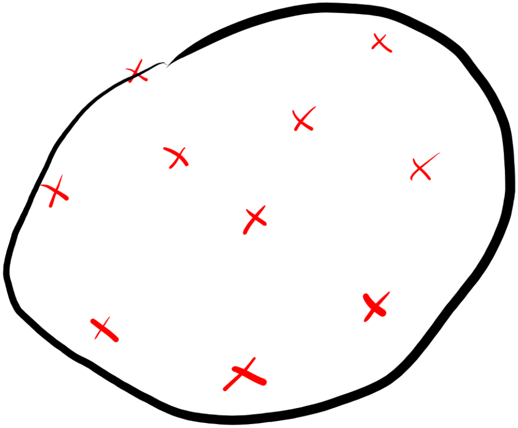
Overfitting



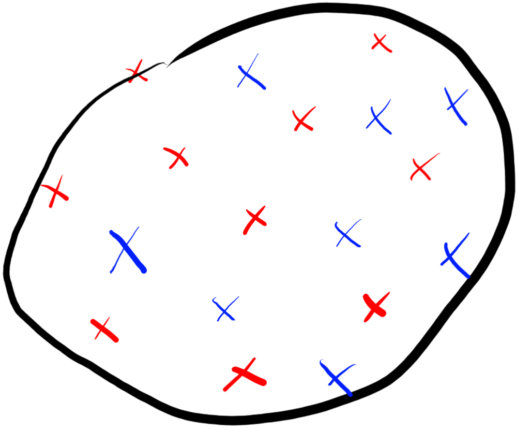
Goodfellow et al., 2016



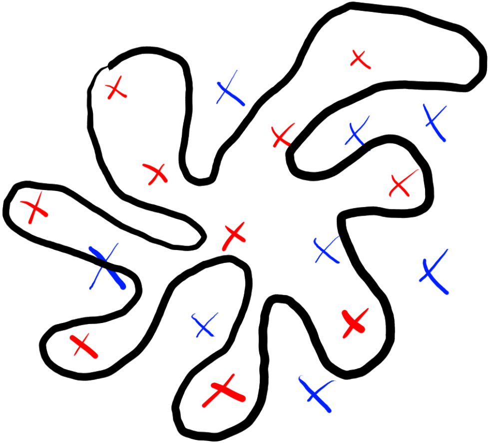
Train set



A good fitted model



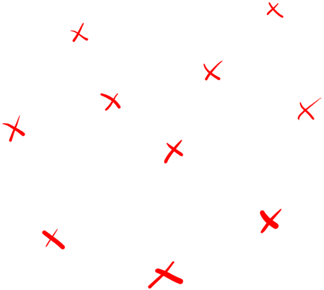
Test set



Overfitting

Biases

Biases in the train set



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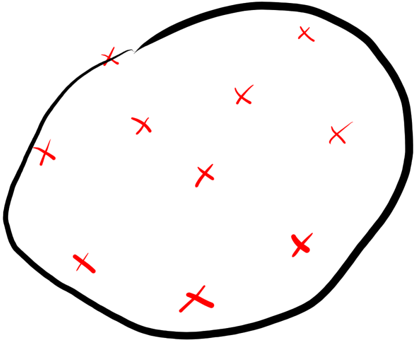

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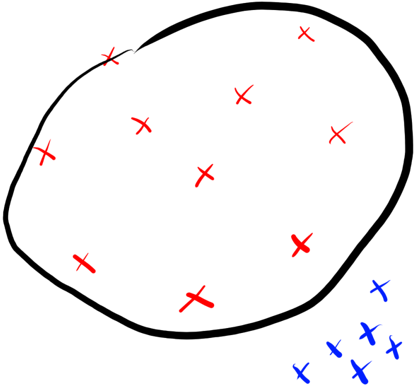

Biases in the train set : Autocorrelation

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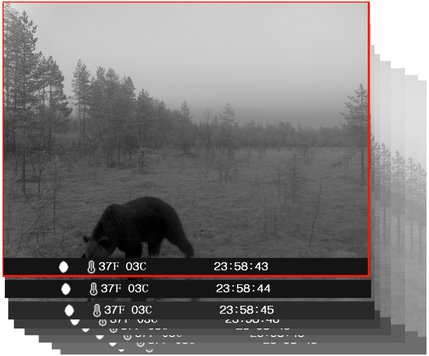

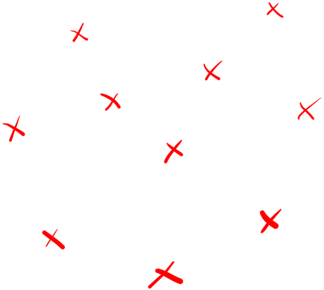

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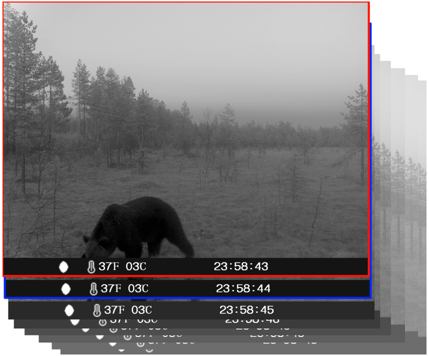

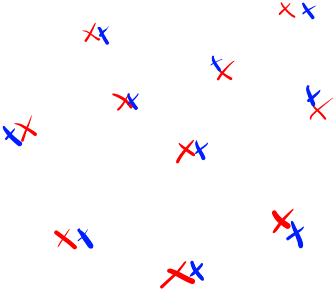

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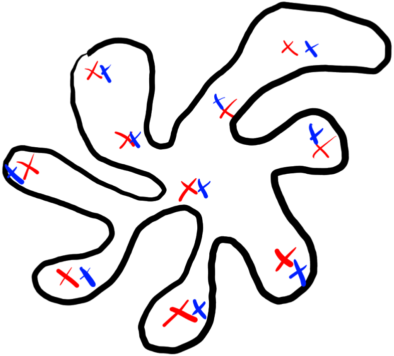

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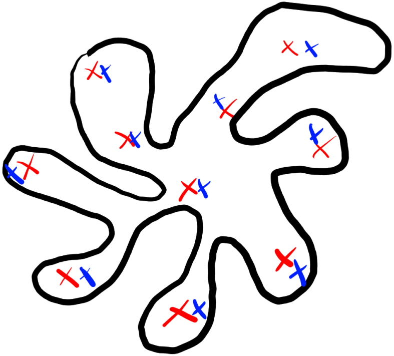
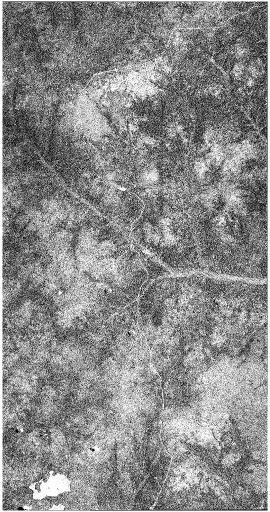


Biases in the train set : Spatial autocorrelation



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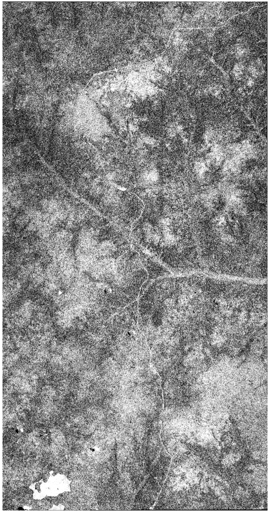

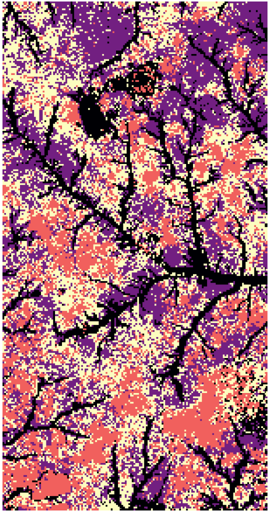

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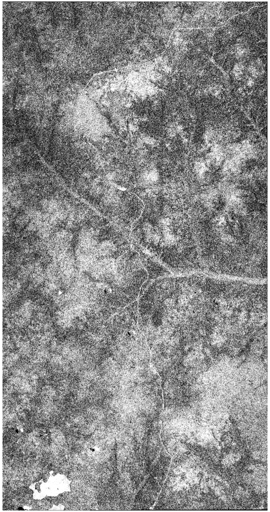

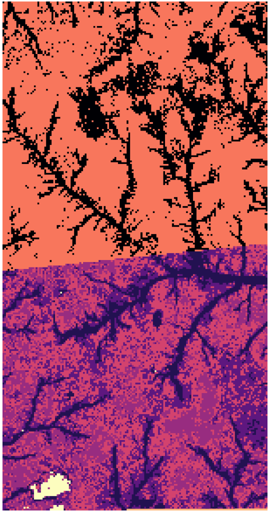

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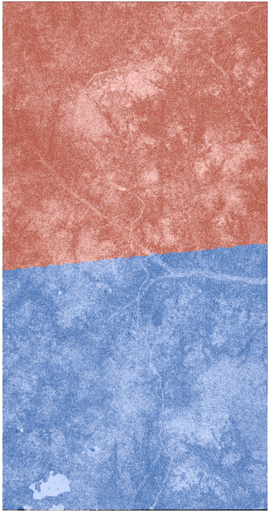

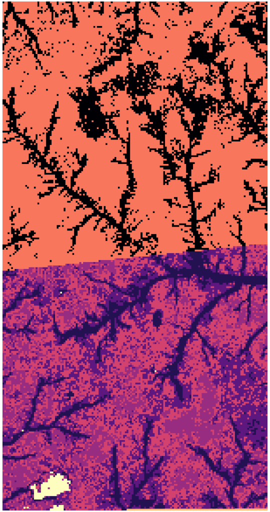

Unbalanced data

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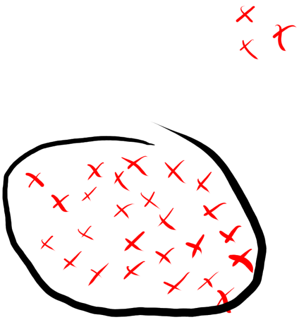

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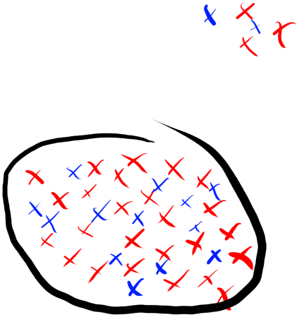

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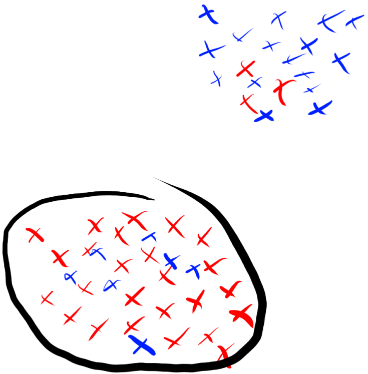

Deal with unbalanced data

- Oversample ?

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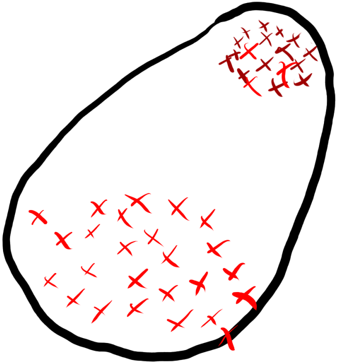
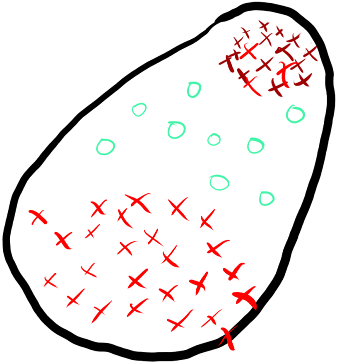


Deal with unbalanced data

- Oversample ?

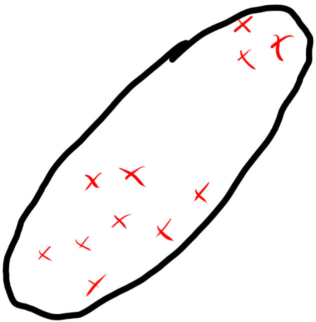


Deal with unbalanced data

- Oversample ?
- Undersample/saturate ?

Deal with unbalanced data

- Oversample ?
- Undersample/saturate ?



Deal with unbalanced data

- Oversample ?
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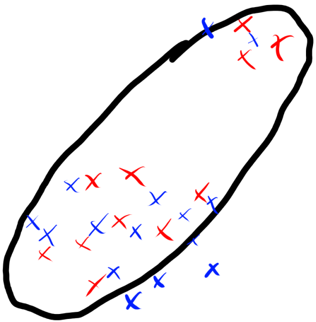
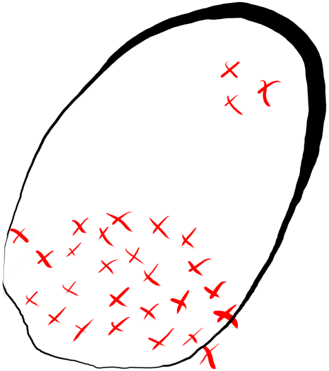


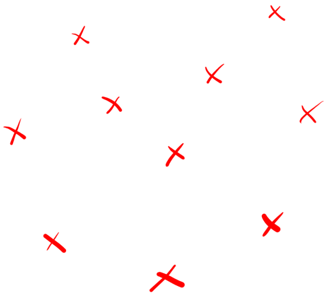
Deal with unbalanced data

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



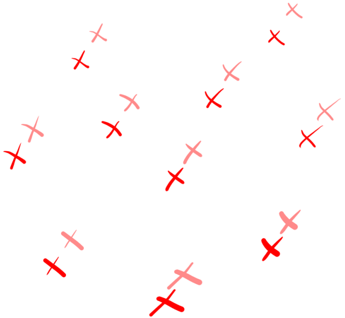
Deal with lack of data

- Data augmentation



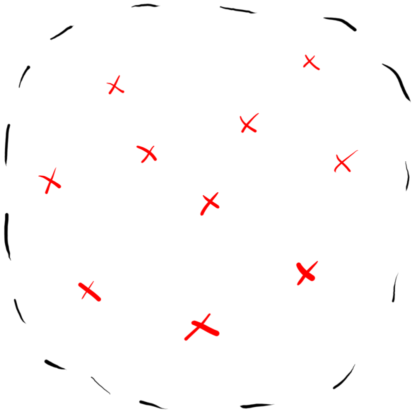
Deal with lack of data

- Data augmentation



Deal with lack of data

- Data augmentation
- Pretrained model

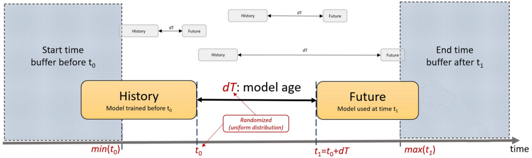


Deal with lack of data

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

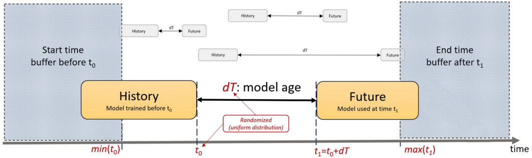
Out of distribution

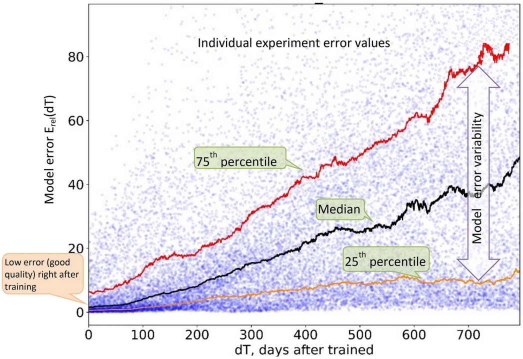
Out of distribution : Evolution with time



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/invade 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

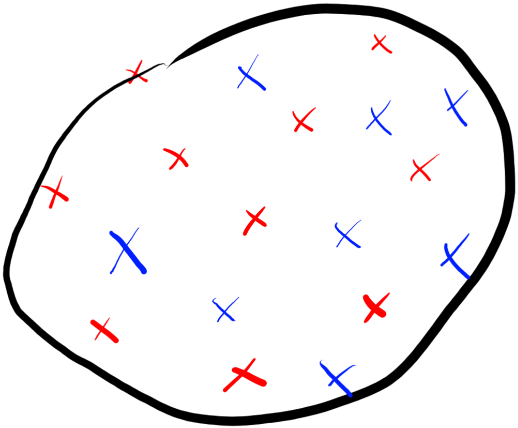
New unknown species in the training test appears in a region.

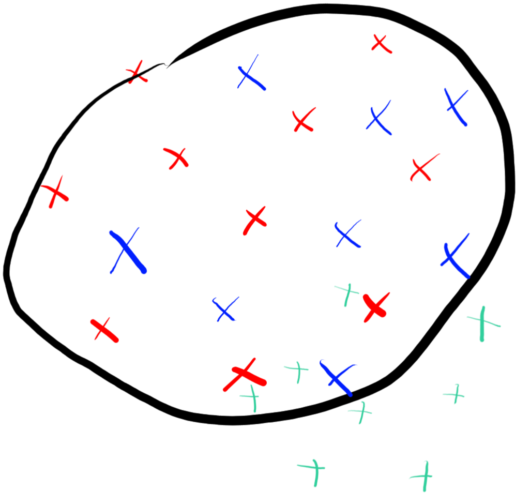
- False Positive : confusion with known species
- False Negative : model misses the new species

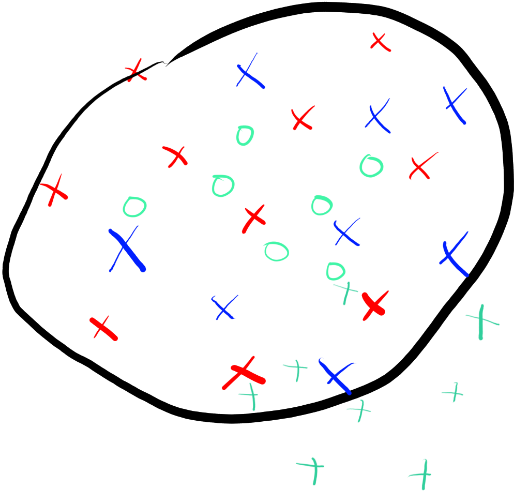
Out of distribution : Invasive species

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 ?

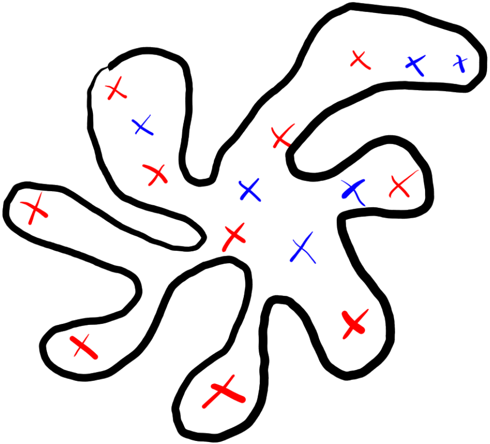
"random split training validation 80/20"

For the uncurated dataset, we randomly sample 142 million images

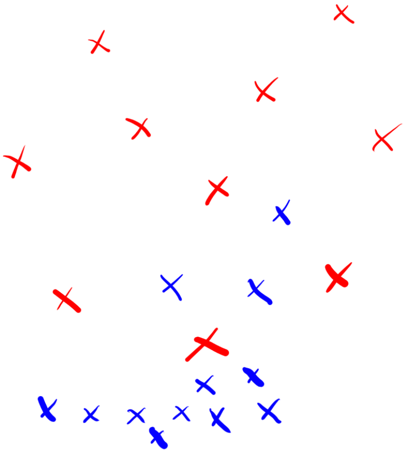
Oquab et al., 2023

Works for huge DL papers, maybe not for you

Overfitting the test set



Overfitting the test set



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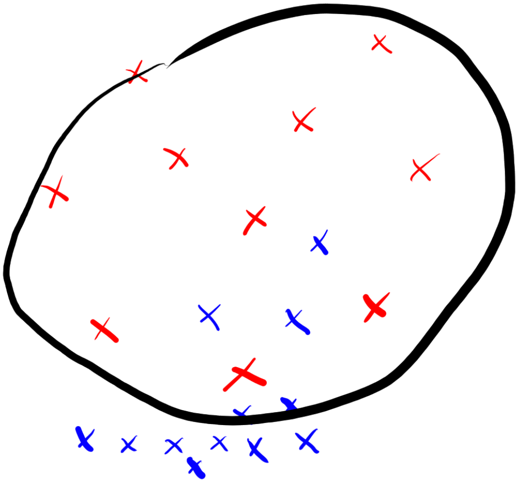

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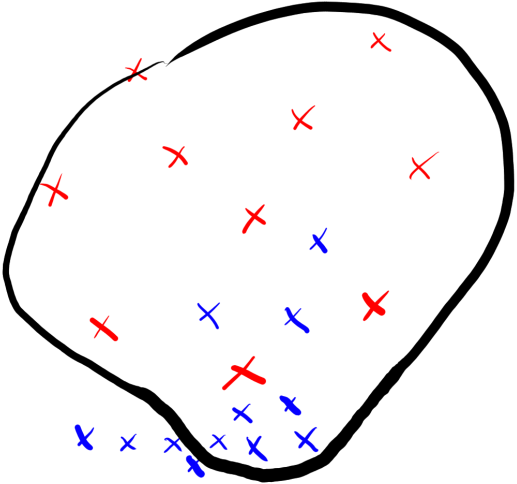

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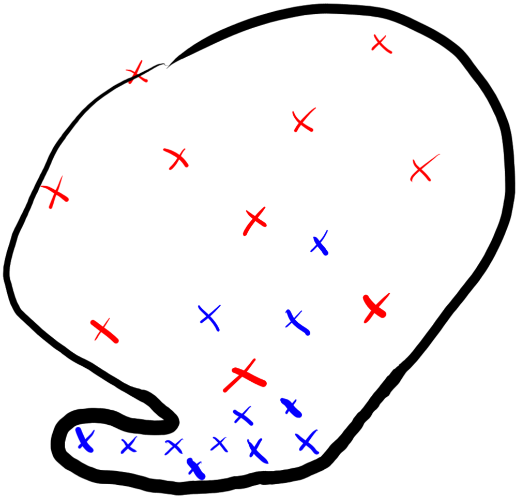

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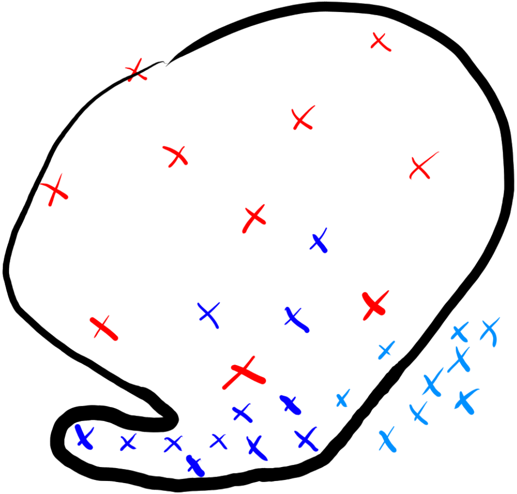

Cross-validation

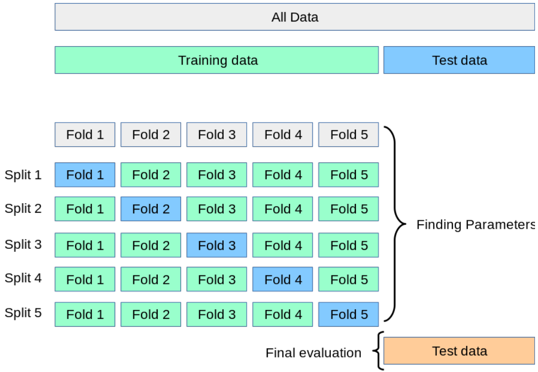

Figure from scikit-learn docs

Cross-validation

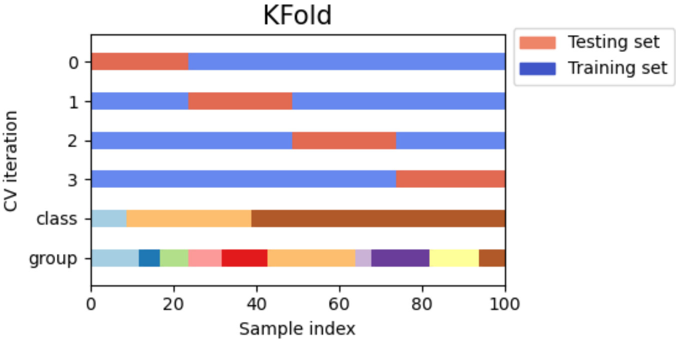

Figure from scikit-learn docs

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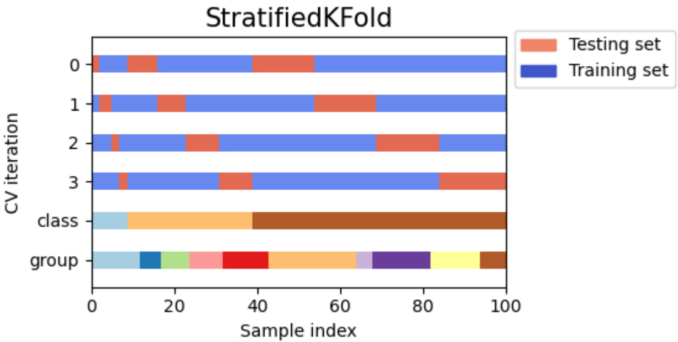
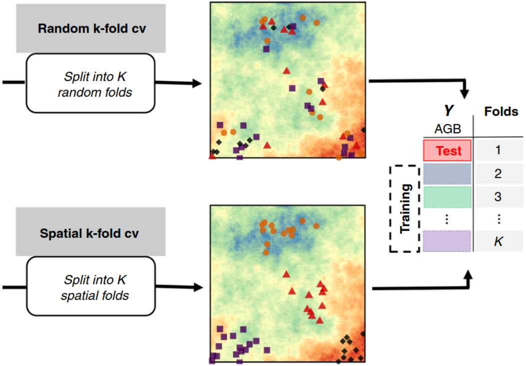


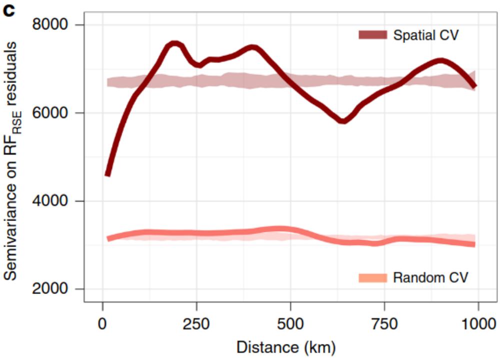
Figure from scikit-learn docs

Spatial cross-validation



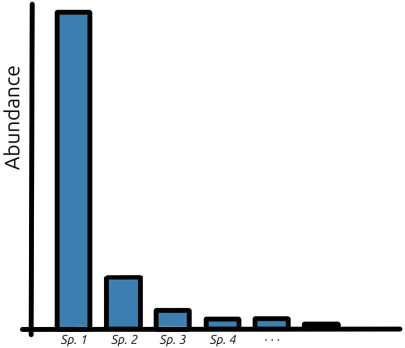
See. Ploton et al., 2020

Spatial cross-validation

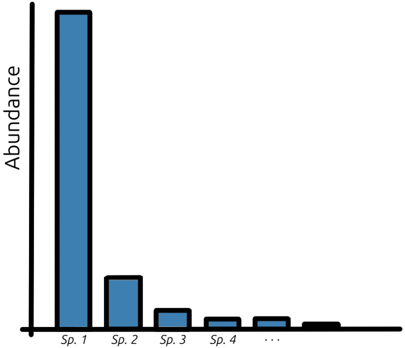


See. Ploton et al., 2020

Choosing the right metric



Choosing the right metric

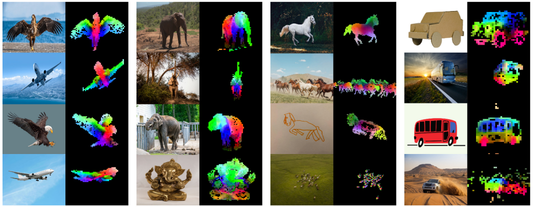


If we predict Sp. 1 all the time:

$$\begin{aligned} \text{Accuracy} &= 0.75 \\ \text{Average precision} &= 0.05 \end{aligned}$$

Perspectives

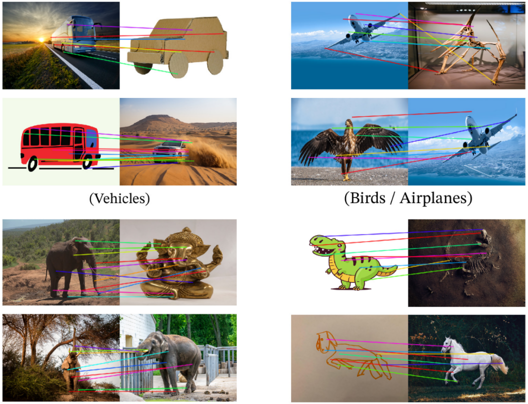
Models are more robust and generalist


(a) (b) (c) (d)

- Self-supervised Learning (Pre-training)

Oquab et al., 2023

Models are more robust and generalist



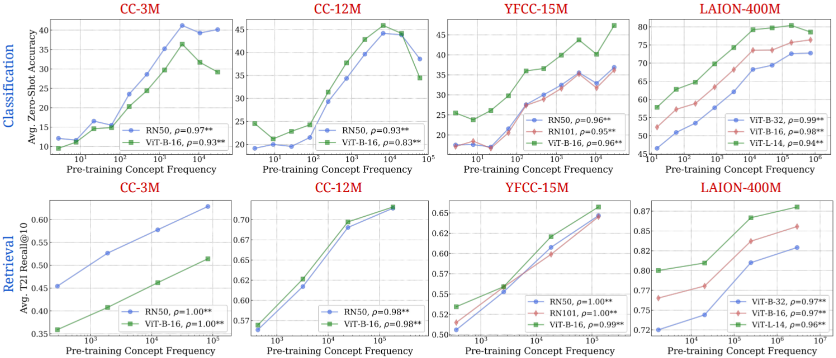
(Vehicles) (Birds / Airplanes)

(Elephants) (Drawings / Animals)

Oquab et al., 2023

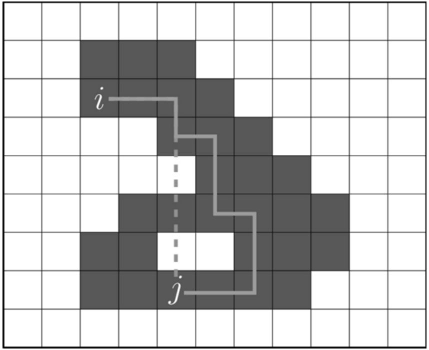
- Self-supervised Learning (Pre-training)
- Better performances and robustness

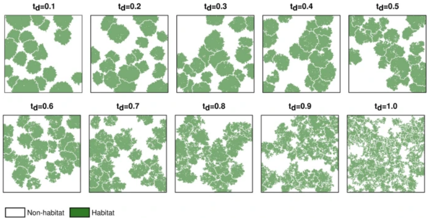
Zero-shot at a cost



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
- ✓ Low-level data
- ✓ Cumbersome but (relatively) easy to analyse

- × Need for explainability
- × **Need for certainty**
- × **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.

Safonova, Anastasiia et al. (2023). **"Ten deep learning techniques to address small data problems with remote sensing".** In: *International Journal of Applied Earth Observation and Geoinformation* 125, p. 103569.

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.