

# Deep learning in practice

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THIS IS YOUR MACHINE LEARNING SYSTEM?

YUP! YOU POUR THE DATA INTO THIS BIG  
PILE OF LINEAR ALGEBRA, THEN COLLECT  
THE ANSWERS ON THE OTHER SIDE.

WHAT IF THE ANSWERS ARE WRONG?

JUST STIR THE PILE UNTIL  
THEY START LOOKING RIGHT.



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In every discipline theory and practice are important. In deep learning, practice is essential.

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This state of affairs can of course be a problem in domains where security and interpretability are important, such as clinical applications.

## General workflow

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- Only at the end: test!

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## Representing your problem

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- Define a validation procedure

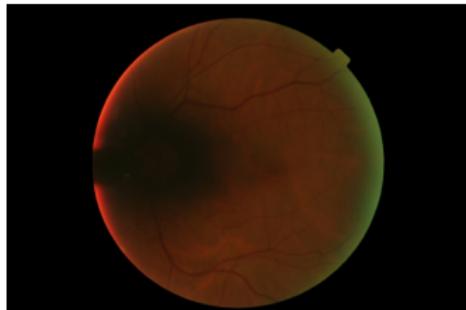
# Example: eye fundus image quality [Alais et al., 2020]



Good quality

## Problem definition

Quality criterion defined by the end-user: are the macula and peripheral vessels visible?



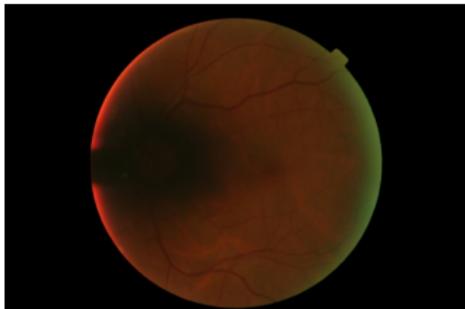
Low quality

Credits: images from the OPHDIAT database

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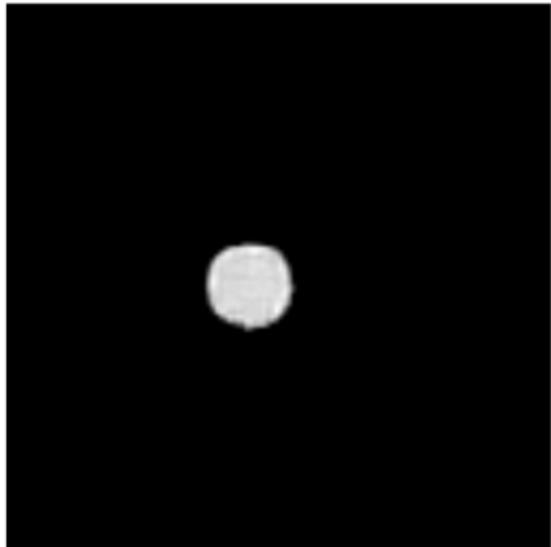
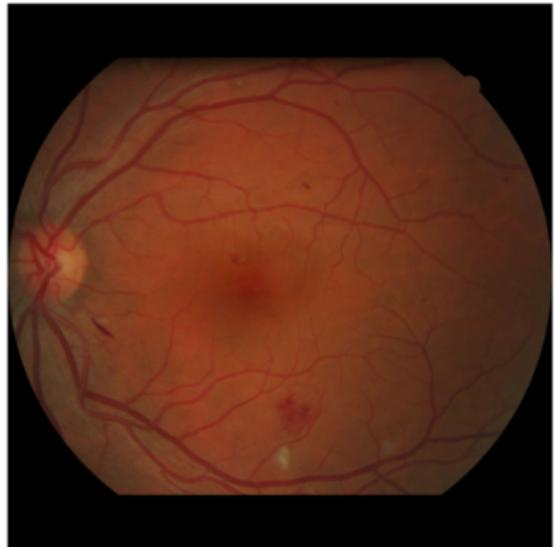
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Quality criterion defined by the end-user: are the macula and peripheral vessels visible?

- First solution: global classification (is the macula visible?)
- Second solution: regression (macula center coordinates)
- Third solution: macula segmentation

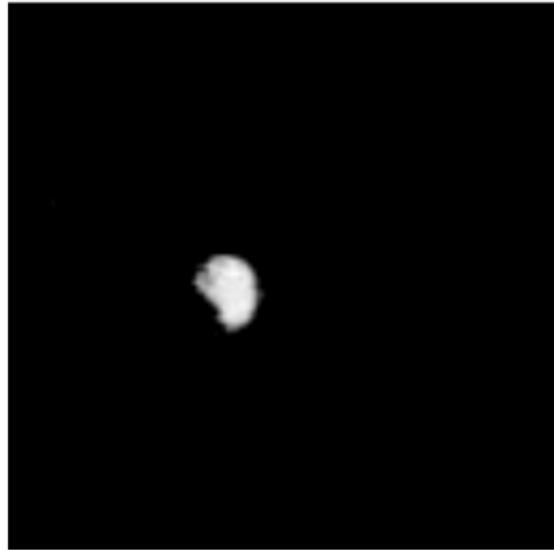
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## Example 1



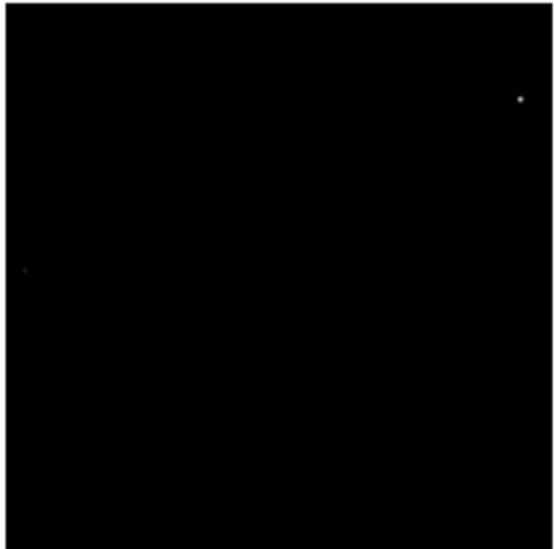
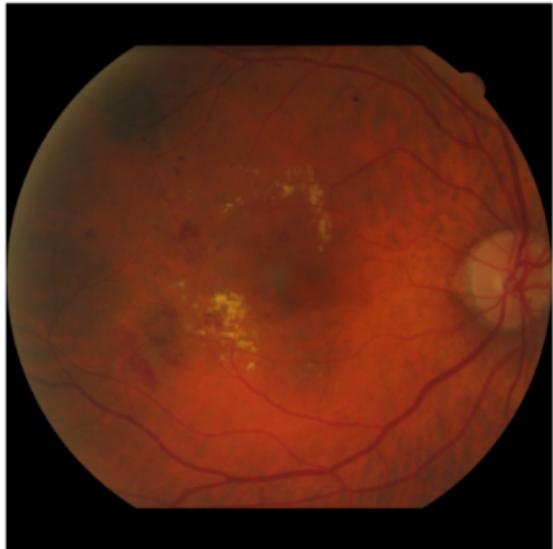
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## Example 2



Credits: images from the OPHDIAT database

## Example 3

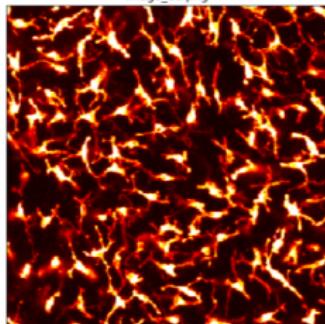


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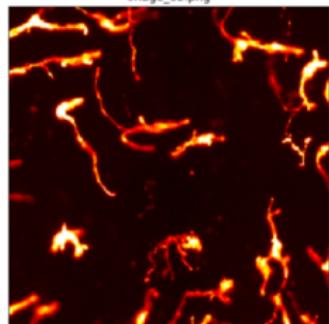
# Counting cells

image

image\_60.png

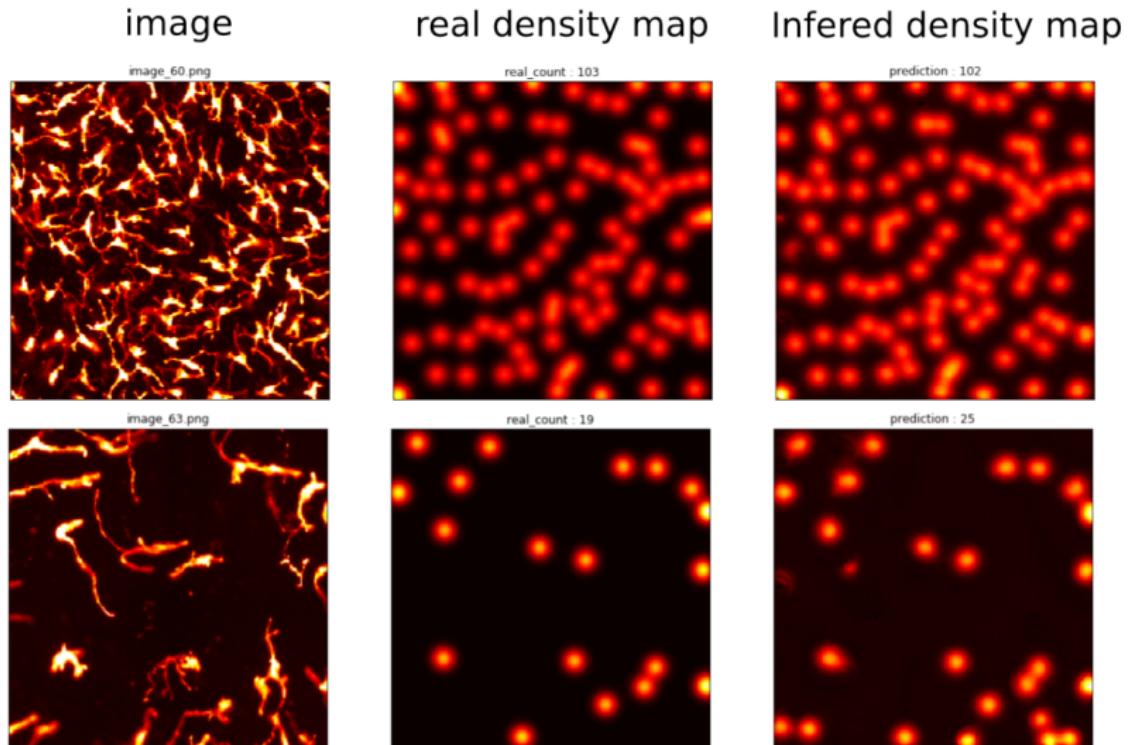


image\_63.png



Credits: Tristan Lazard, master thesis. In collaboration with L'Oréal.

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## Performance evaluation

- Define an objective
- Choose the right metrics and try to use a loss function that is as close as possible to these metrics

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Is database constitution the main step?

- In practical, real-world applications, this is the most time-consuming step
- If the data set does not conveniently represent your problem you will run into difficulties

↑↓ François Chollet a retweeté



Andrew Ng ✅ @AndrewYNg · 11h

...

I'm with [@fchollet](#) on this. There're some best-practices on creating and organizing data that experienced applied ML people use, but we still need to flesh out and widely disseminate these ideas. This will be key to getting more ML systems deployed.



François Chollet ✅ @fchollet · 24 janv.

ML researchers work with fixed benchmark datasets, and spend all of their time searching over the knobs they do control: architecture & optimization. In applied ML, you're likely to spend most of your time on data collection and annotation -- where your investment will pay off.

[Afficher cette discussion](#)

19

↑↓ 117

685



## Anecdote: tank detection

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... but in fact images containing tanks were acquired during sunny days, while images without tanks were shot with overcast weather. The network was simply detecting lighter images!

This anecdote might be a urban legend, but nevertheless is a good illustration of the problems one might run into during database preparation. More information available from:

<https://www.gwern.net/Tanks>

## What quality is needed for the ground-truth?

- Deep learning models tend to be robust with respect to ground-truth errors
  - if they are not too frequent
  - and if they are not systematic.
- In the case of segmentation, you do not need a pixel-precision high quality segmentation [Heller et al., 2018]

## Preprocessing

- Standard statistical preprocessing: not always useful, and sometimes problematic, when applied to images. It is often enough to divide by 255!
- Use other preprocessing only if really necessary.

# Data augmentation

- Geometrical transformations: similarities
- Elastic transformations
- Noise
- Grey level or colour modifications
- AugMix, CutMix, etc. (cf. lesson on optimization)
- Specific methods: articulated objects, . . .

## Example: plankton classification

Plankton classification: hundred classes - a few dozen examples per class.

Data augmentation:

- Geometric transformations
- Detect joints and simulate their functioning



Credits: Kaggle plankton classification challenge (<https://www.kaggle.com>)

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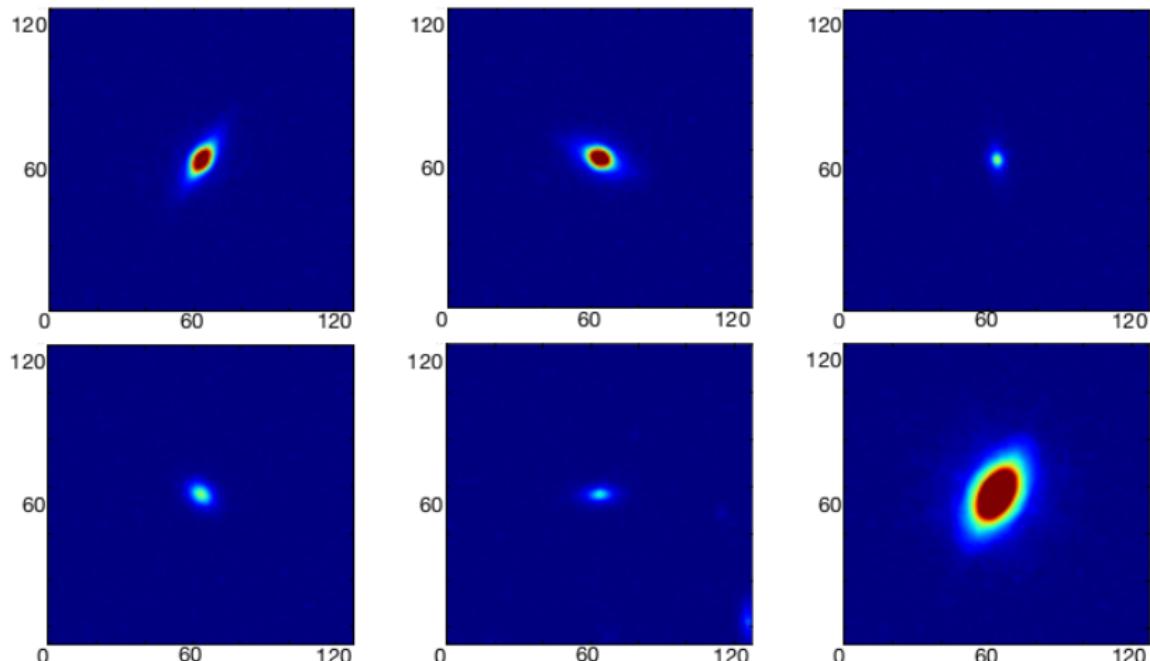
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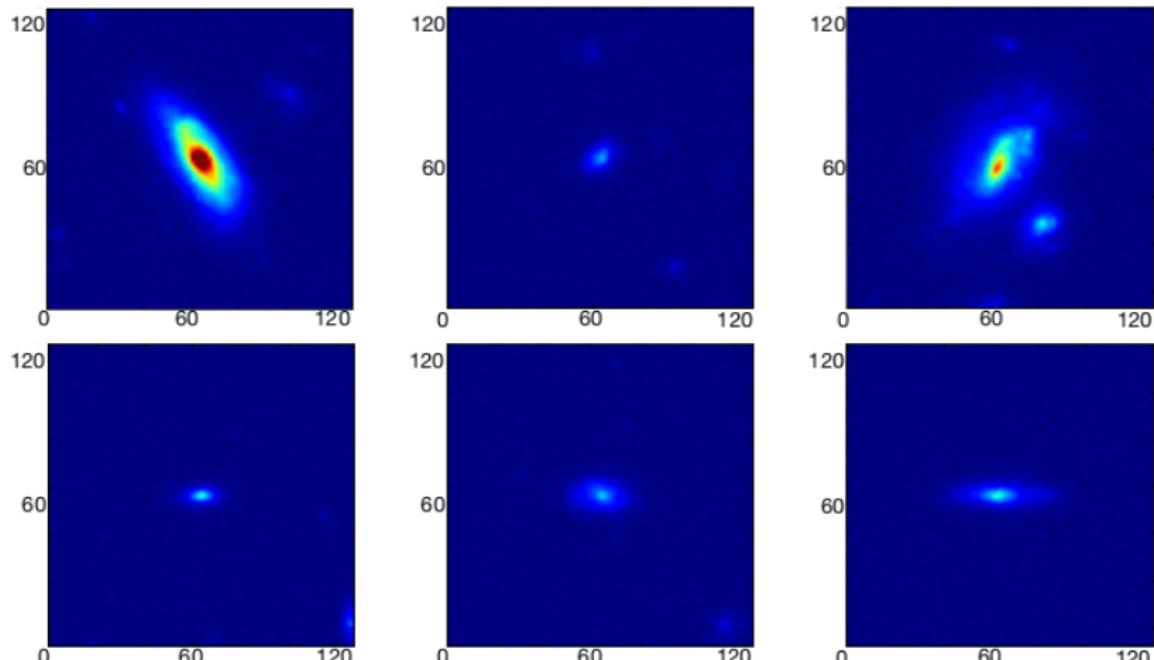
- Using simulated data is convenient...
- ... but it has to be as similar as possible to the real data
- A transfer learning method with real data will probably be necessary
- Your test data should be real

## Example [Tuccillo et al., 2018]



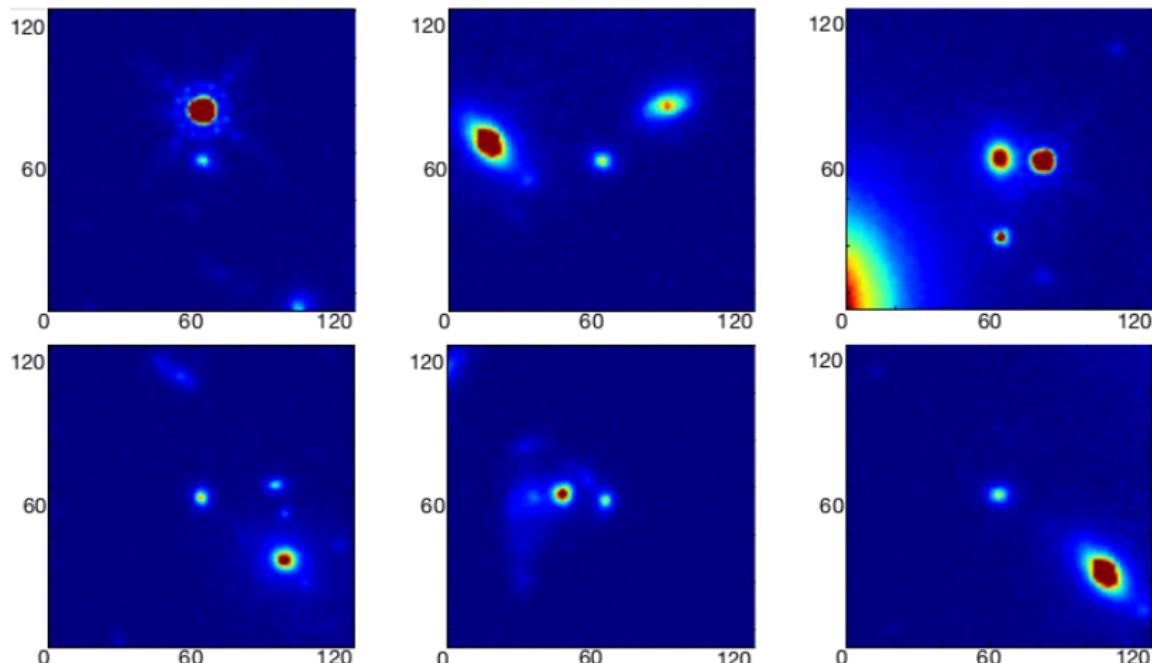
Simulated images

## Example [Tuccillo et al., 2018]



Well-fitted images

# Example [Tuccillo et al., 2018]



Poorly fitted images

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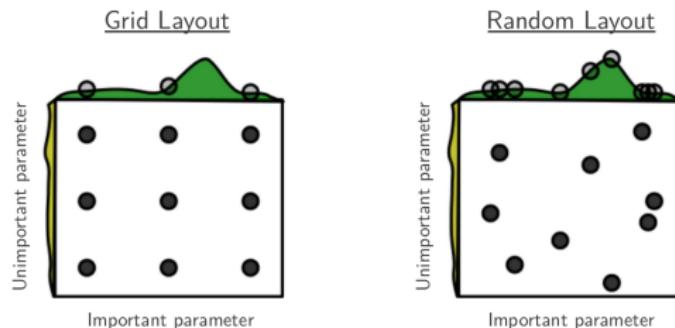
- Begin with a standard architecture
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U-Net
  - Instance segmentation: Mask R CNN
- If you are dealing with a complex problem, start with pre-learned weights and use transfer learning to adapt them to your application

## Optimizing your model

- Choose an optimizer
- Use regularization ( $L_1$ ,  $L_2$ , dropout, noise layer ...)
- Add batch normalization if convergence is difficult

# Hyperparameters tuning

- Manual tuning: might work if the number of parameter is small and the experience of the developer/researcher high
- Automatic tuning:
  - Grid search
  - Random search
  - Population based approaches
  - Etc.



## Computing power

DL became feasible in practice thanks to the use of Graphical Processing Units (GPU). Beyond theoretical research on the subject, to work with DL you need specific hardware:

- CPUs: with many of them, and using libraries that allow parallelization, this could be a solution - in practice, it is seldom done.
- GPUs: this is the most common solution adopted for deep learning.
- TPU: Tensor Processing Units are integrated circuits specifically developed by Google for deep learning.

## Computing power

- DL research and development is extremely computationally time-consuming.
- However, running predictions with an already optimized model is much faster

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## Problem formulation

In computer vision:

- Databases can be huge, requiring substantial computing power and making learning complex
- In many practical applications the learning data base can be small

Transfer learning brings a solution to these problems.

## Definitions [Pan and Yang, 2010]

### Domain and task

- A domain  $D$  is a probability space  $(X, P)$ , where  $X$  is finite.
- Given a domain  $D = (X, P)$ , a task  $T$  consists of two components: a label space  $\mathcal{Y}$  and a function  $f : X \rightarrow \mathcal{Y}$ , that is only known on a training set  $\{(x_i, y_i), 1 \leq i \leq n, x_i \in X, y_i \in \mathcal{Y}\}$ .

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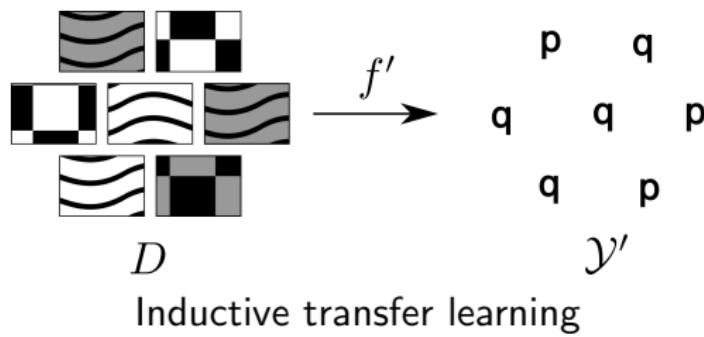
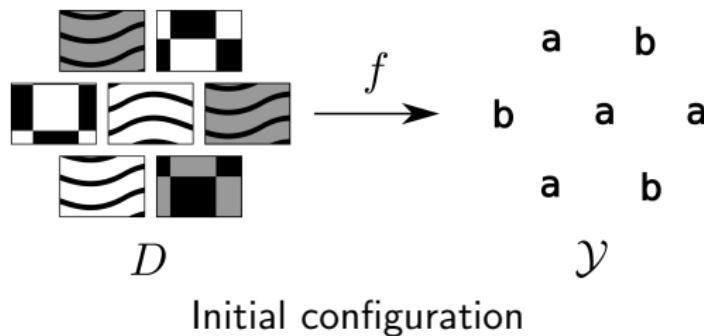
### Transfer learning

Let us consider

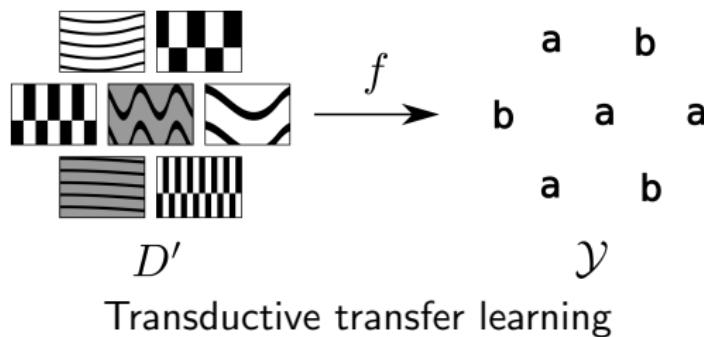
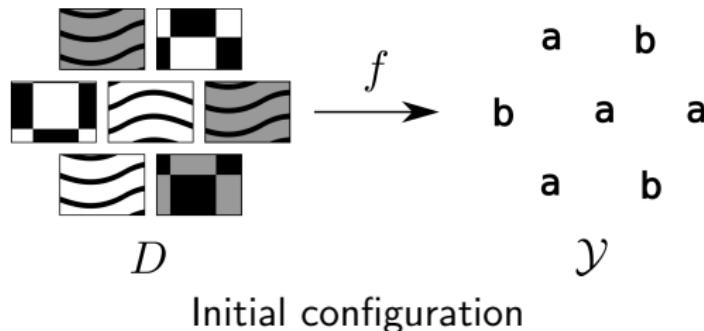
- a *source* domain  $D_S$  and a task  $T_S$  on that domain, and
- a *target* domain  $D_T$  and a task  $T_T$  on that domain.

Transfer learning from  $(D_S, T_S)$  to  $(D_T, T_T)$ , where  $D_S \neq D_T$  or  $T_S \neq T_T$ , consists in using the knowledge in  $(D_S, T_S)$  to improve the learning of task  $T_T$ .

## Types of transfer learning: inductive

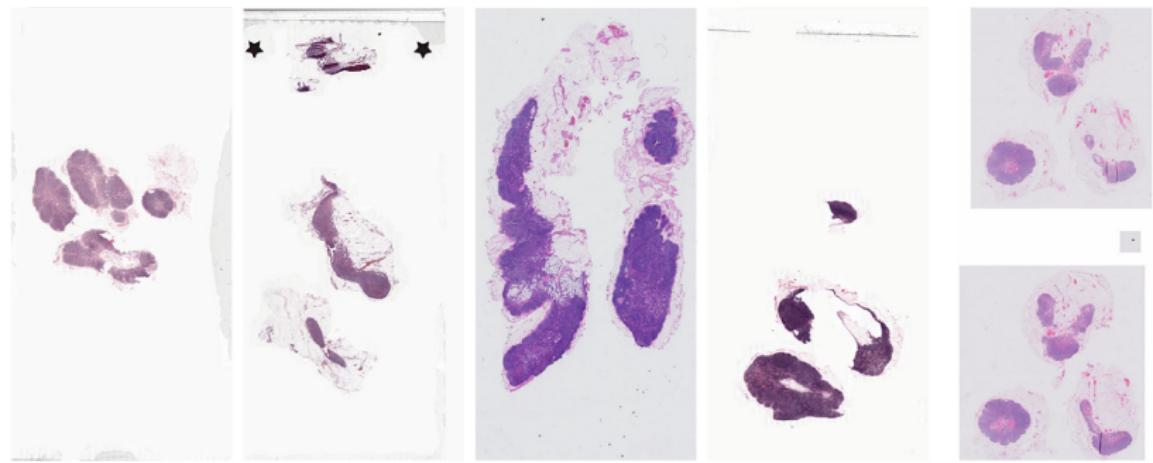


## Types of transfer learning: transductive



Also known as domain adaptation.

## Example of domain shift



Images from the Camelyon dataset [Litjens et al., 2018]

## Transfer learning through fine-tuning

Suppose that thanks to a training set  $(X_0, \mathcal{Y}_0)$  a model  $f_{\theta_0}$  has been learnt.

Transfer learning through fine-tuning consists in learning another model  $f_\theta$  from a training set  $(X, \mathcal{Y})$  using as starting point  $f_{\theta_0}$ . For transfer learning to work, both training sets have to be somehow related and compatible.

## General procedure

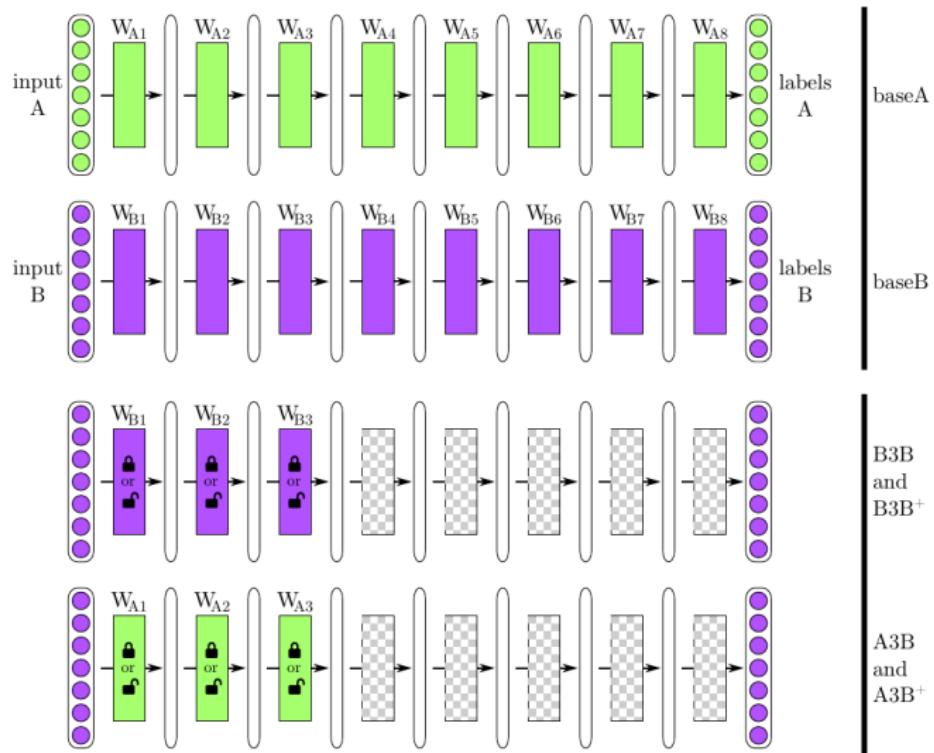
- Choose an existing model, optimized on a data base such as ImageNet. It should be able to process the new data
- Remove the last layers of the model and replace them with layers adapted to the task at hand
- Fine-tune the resulting model
  - Note that some pre-trained layers are often *frozen*

## A reference paper [Yosinski et al., 2014]

Jason Yosinski, Jeff Clune, Yoshua Bengio, Hod Lipson. **How transferable are features in deep neural networks?** Neural Information Processing Systems, 2014.

The authors devised experiments on the ImageNet database in order to evaluate different fine-tuning strategies and improve our understanding of these methods.

# Experiments configuration

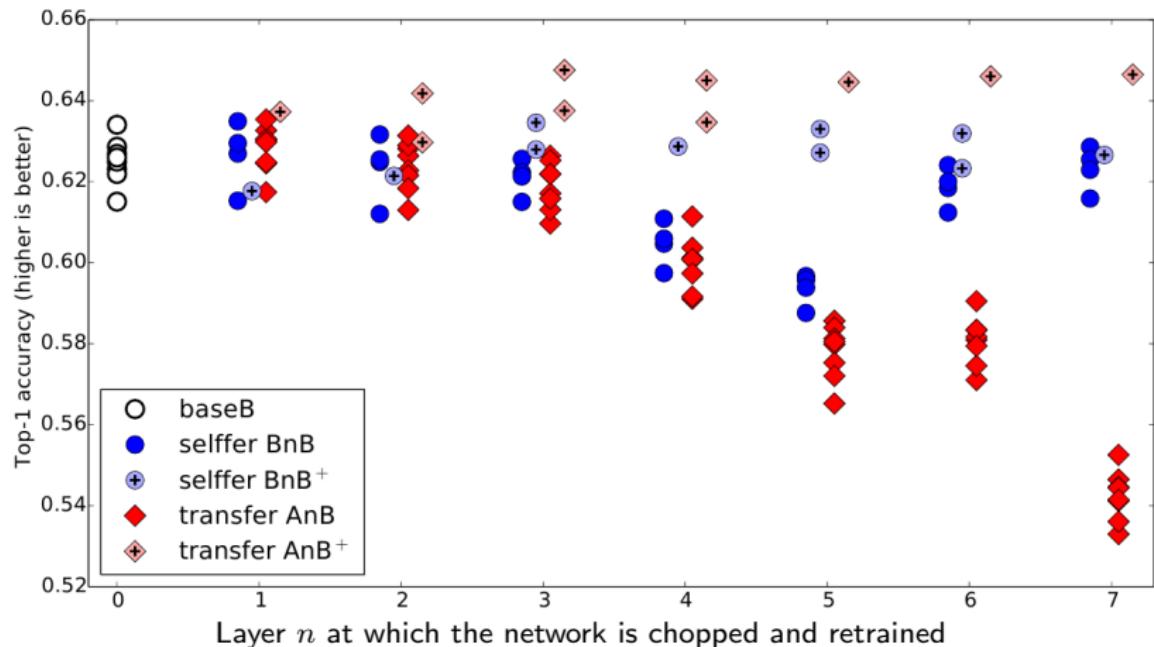


## First experiment configuration

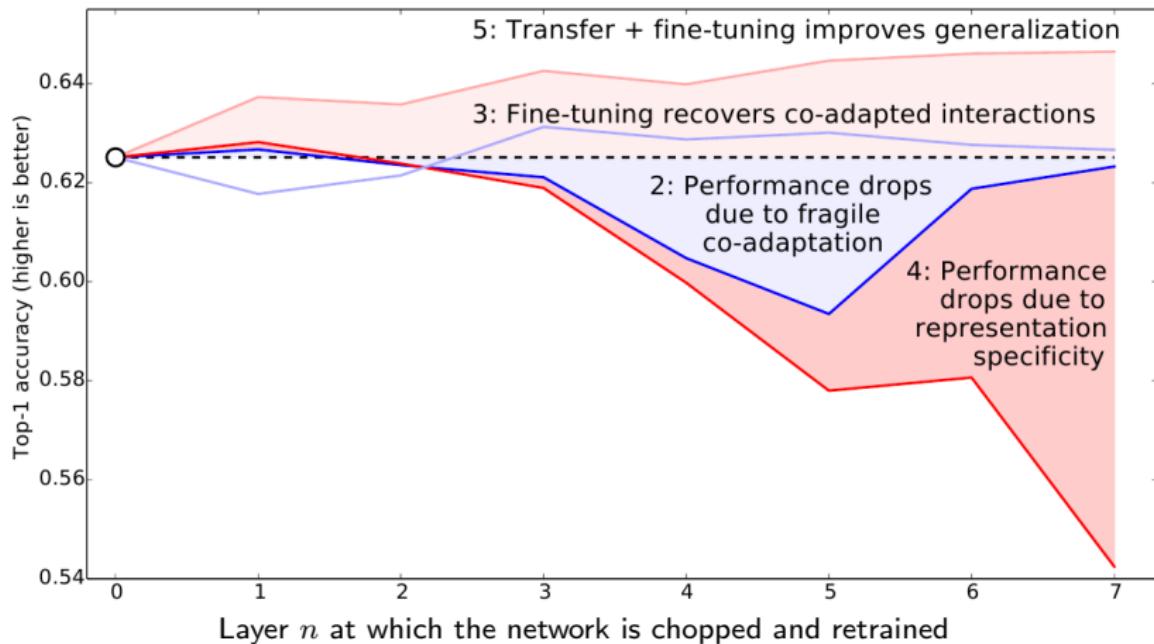
### ImageNet data set split

- Set A: 500 randomly selected classes
- Set B: 500 other classes

## First experiment results



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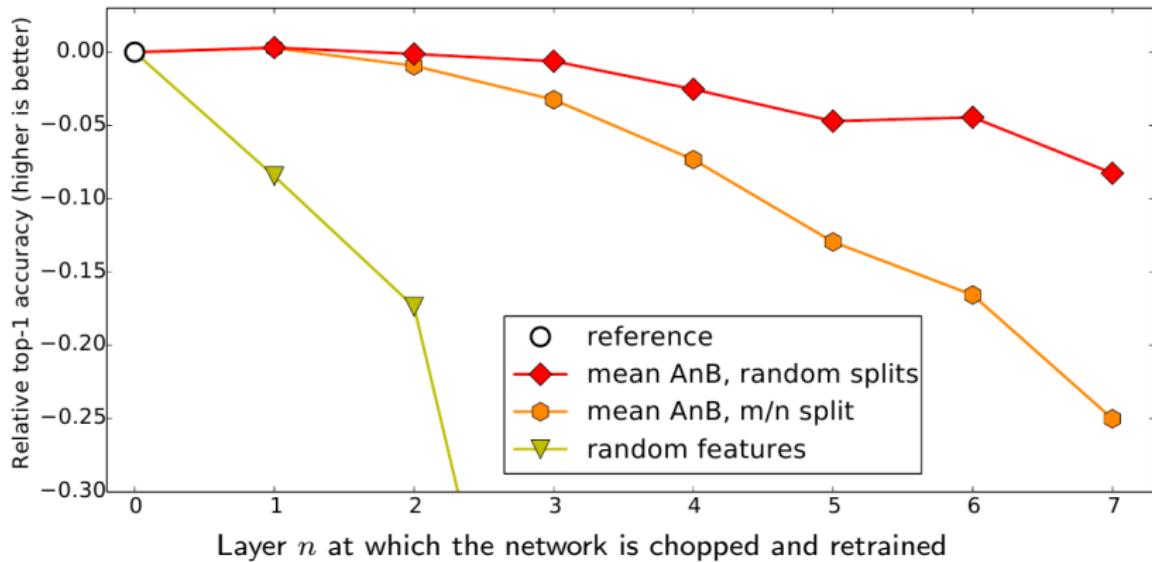


## Second experiment configuration

### ImageNet data set split

- Set A: Man-made objects (551 classes)
- Set B: Natural entities (449 classes)

## Second experiment results



## Experiments conclusions

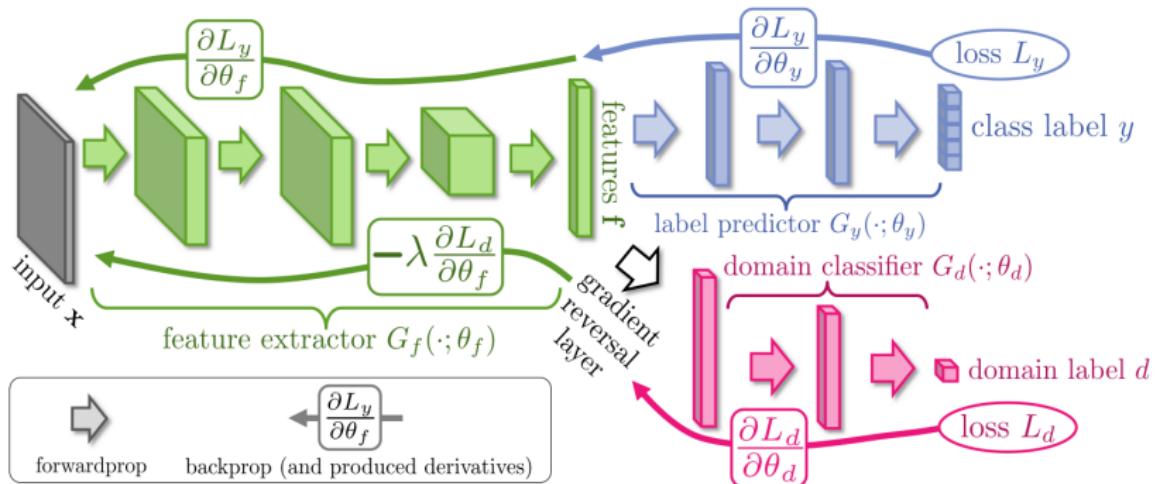
- Two separate issues with transfer learning:
  - Specificity of high level features
  - Co-adaptation of neurons on neighboring layers
- Transfer learning is less efficient when the sets are more dissimilar (at least when the pre-trained weights are frozen)
- Generalization performance can be boosted by transfer learning

# Unsupervised domain adaptation

	MNIST	SYN NUMBERS	SVHN	SYN SIGNS
SOURCE				
TARGET				
	MNIST-M	SVHN	MNIST	GTSRB

The labels of the source domain are known, but not those of the target domain. How to proceed ?

## Example method [Ganin and Lempitsky, 2015]



# Results



Method	Source Target	MNIST MNIST-M	SYN NUMBERS SVHN	SVHN MNIST	SYN SIGNS GTSRB
Source only		0.575	0.867	0.592	0.740
Proposed approach		0.815	0.905	0.711	0.887
Train on target		0.989	0.924	0.995	0.998

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## Related subjects

- Foundation models

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### Definition [Bommasani et al., 2022]

“A **foundation model** is any model that is trained on broad data (generally using self-supervision at scale) that can be adapted (e.g., fine-tuned) to a wide range of downstream tasks.”

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- Model distillation

# References |

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