Deep learning in practice

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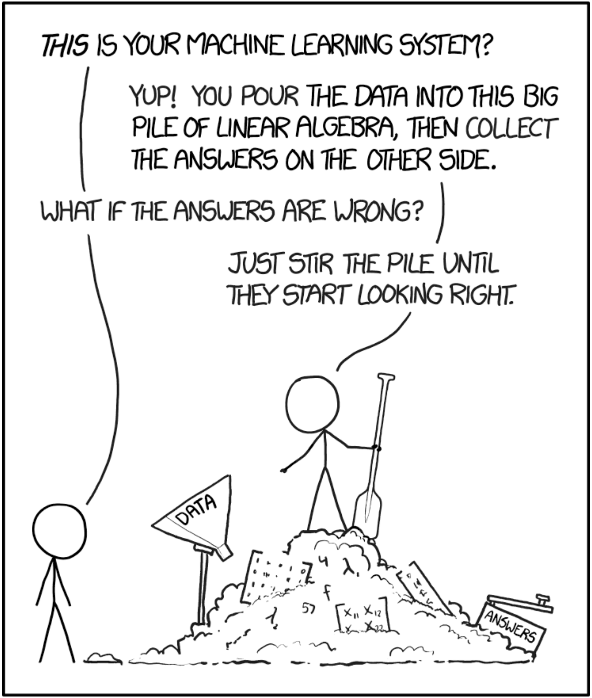

Credits: xkcd.com (CC BY-NC 2.5)

Practicing deep learning

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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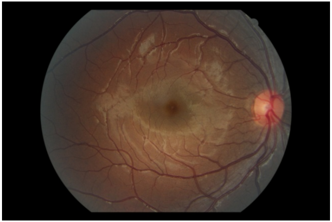
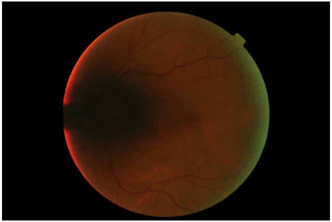
- Define an evaluation procedure

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



Good quality



Low quality

Problem definition

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

Credits: images from the OPHDIAT database

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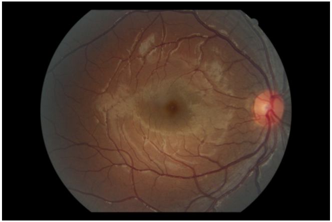

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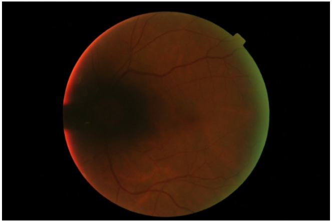

Low quality

Problem definition

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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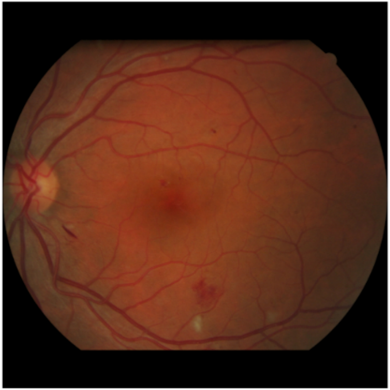
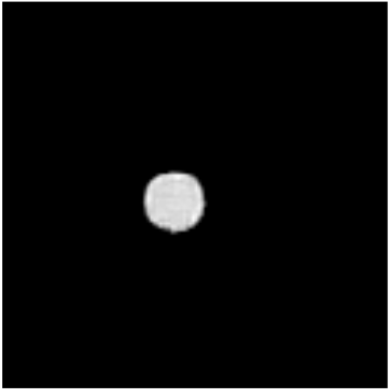
Example 1





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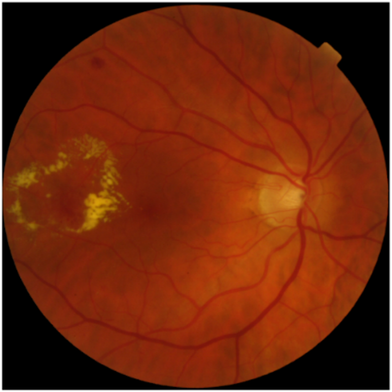
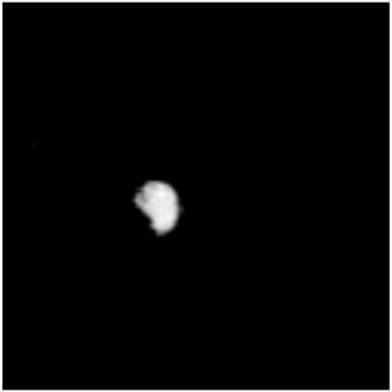
Example 2





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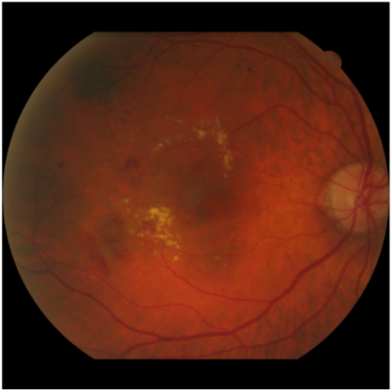

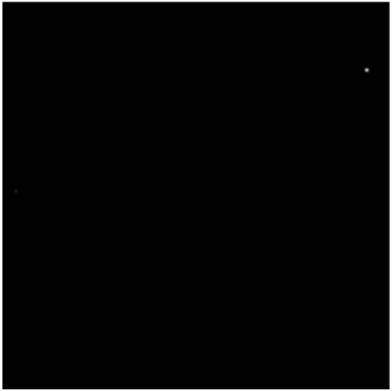

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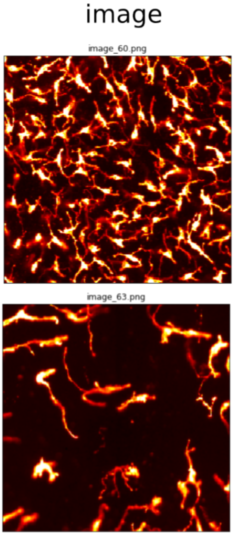
Counting cells



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

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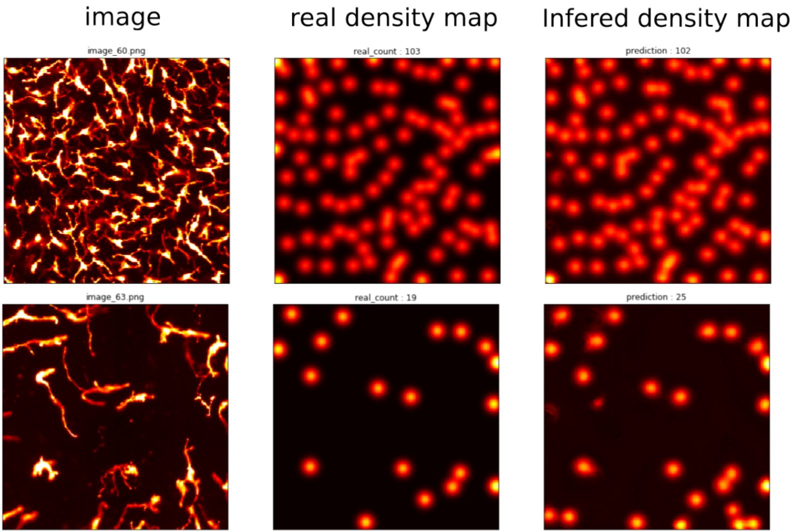

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Performance evaluation

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

Contents

Building the data sets

- Gather your images in order to build a data set that conveniently represents your problem
- How many images do you need?
- Build a proper ground-truth

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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
- 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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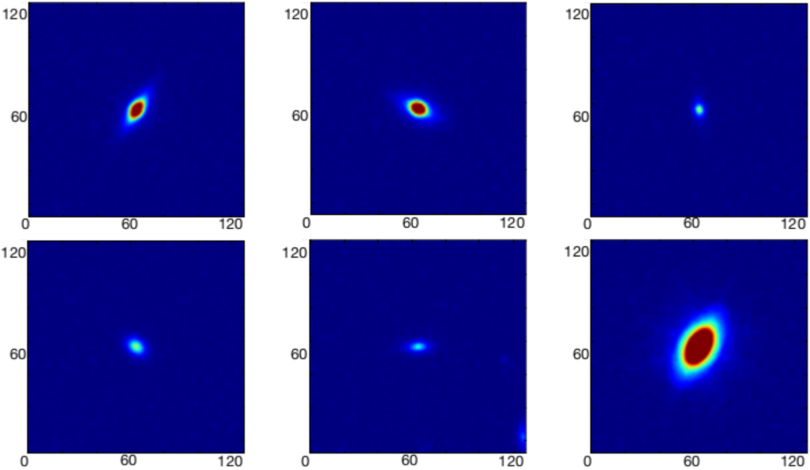
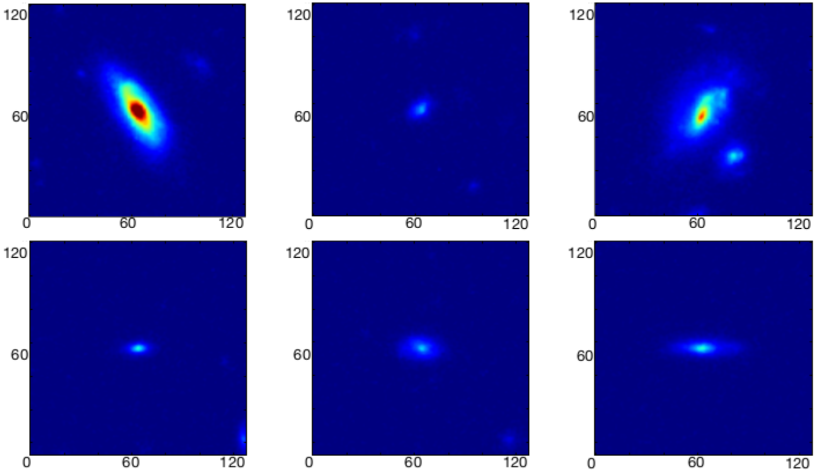
- A transfer learning method with real data will probably be necessary
- Your test data should be real

Example [Tuccillo et al., 2018]



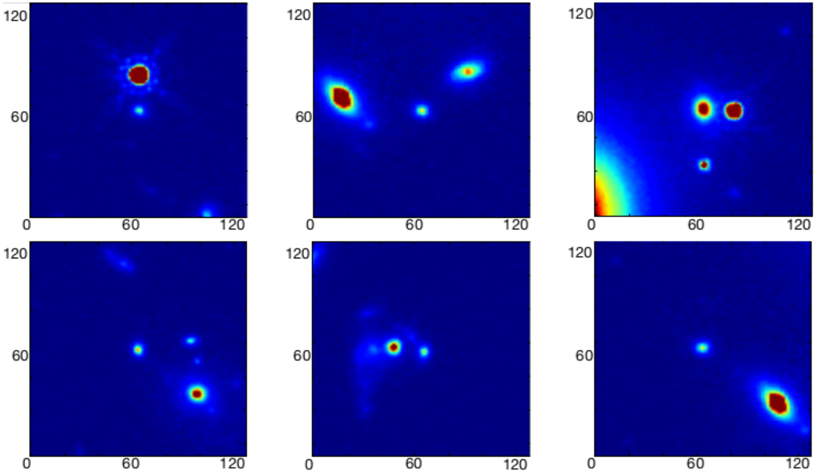
Simulated images

Example [Tuccillo et al., 2018]



Well-fitted images

Example [Tuccillo et al., 2018]



Poorly fitted images

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Architecture choice

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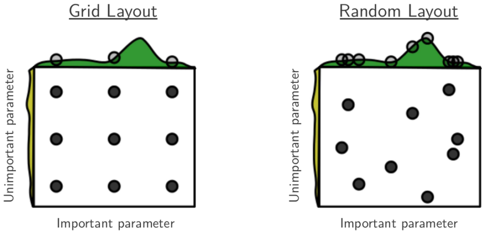
  - Instance segmentation: Mask R CNN
- If you are dealing with a complex problem, start with pre-learned weights and use transfer learning to adapt them to your application

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.



Credits: [Bergstra and Bengio, 2012]

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

Contents

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 $f : X \to \mathcal{Y}$, that is only known on a training set $\{(x_i, y_i), 1 \leq i \leq n, x_i \in X, y_i \in Y\}$.

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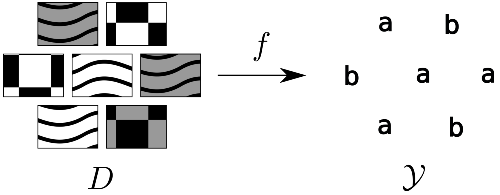
Transfer learning

Let us consider

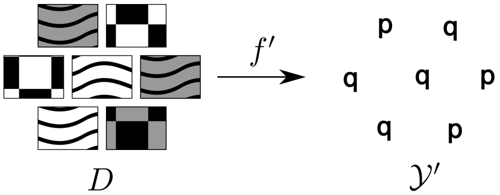
- a *source* domain D_S and a task T_S on that domain, and
- a *target* domain D_T and a task T_T on that domain.

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

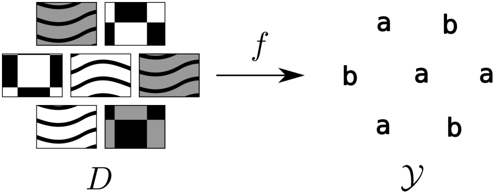


Initial configuration



Inductive transfer learning

Types of transfer learning: transductive



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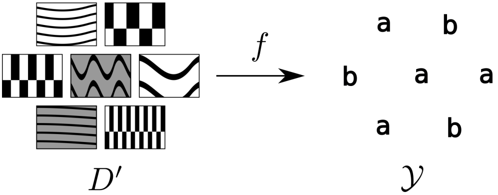
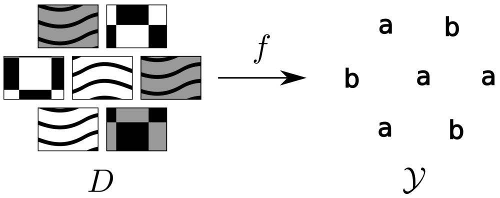


Transductive transfer learning

Also known as domain adaptation.

Types of transfer learning: transductive homogeneous



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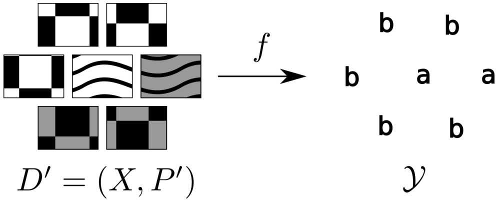
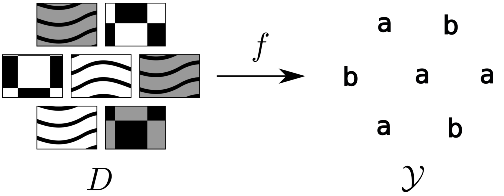


Transductive homogeneous transfer learning

Types of transfer learning: transductive heterogeneous



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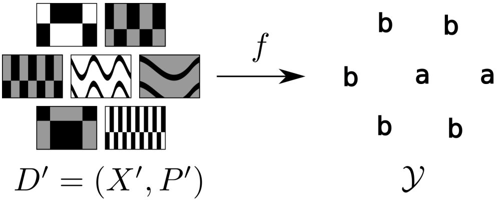


Transductive heterogeneous transfer learning

Transfer learning through fine-tuning

Suppose that thanks to a training set $(X_0, \mathcal{Y}_0)$ a model f_{θ_0} has been learnt.
Transfer learning through fine-tuning consists in learning another model f_θ from a training set $(X, \mathcal{Y})$ using as starting point f_{θ_0}.
For transfer learning to work, both training sets have to be somehow related and compatible.

General procedure

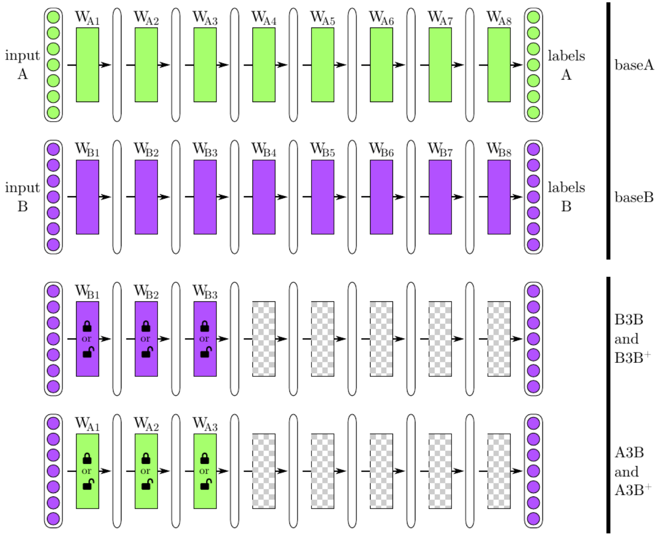
- Choose an existing model, optimized on a data base such as ImageNet. It should be able to process the new data
- Remove the last layers of the model and replace them with layers adapted to the task at hand
- Fine-tune the resulting model
  - Note that some pre-trained layers are often *frozen*

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

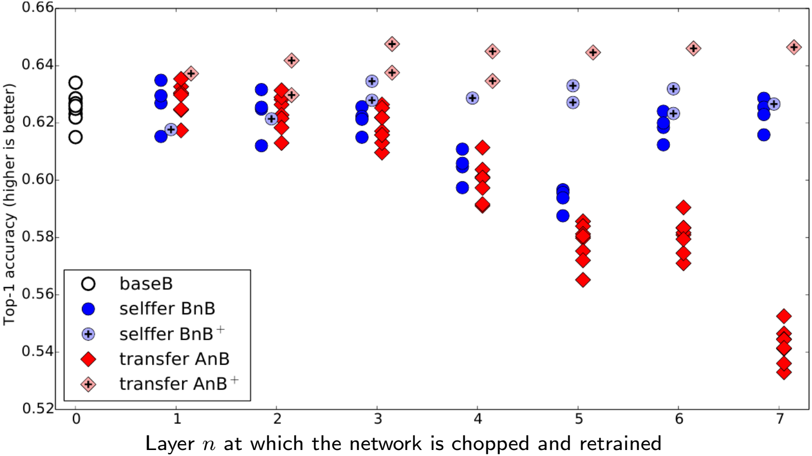


First experiment configuration

ImageNet data set split

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

First experiment results



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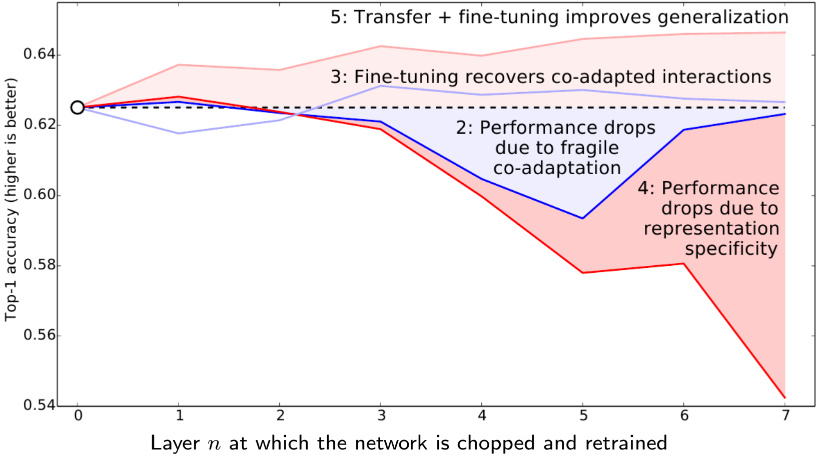
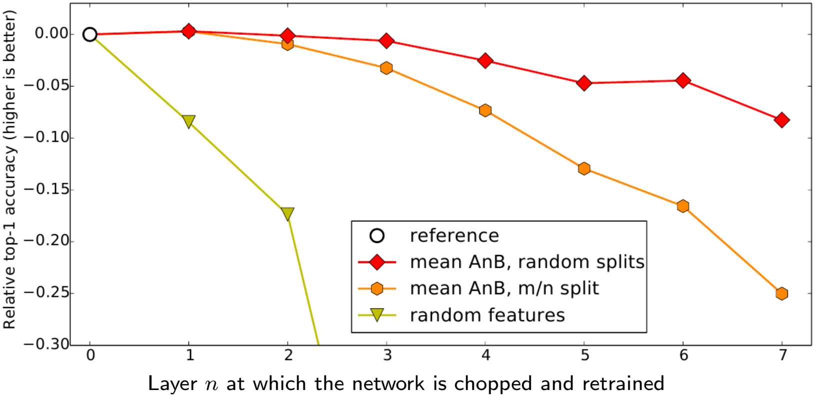


Second experiment configuration

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

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References II

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