Introduction to Deep Learning and Transfer Learning

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Global formalism

Input/output

- Goal: infer a function from an input (often tensor) space to an output (often tensor) space, $\mathbf{y} = f(\mathbf{x})$,
- Example: input can be an image, output a vector where the largest value indicate the category the image belongs to.

Error/Loss

- Loss: nonnegative measure of the discrepancy between expected output $\hat{\mathbf{y}}$ and obtained output $\mathbf{y}$.
- Example: output should be $[0, 1]$ but is $[0.2, 0.8]$.

Parameters

- $f = f_\theta$ contains **parameters** θ to be trained,
- In most cases, an ideal f_θ exists but is **hard to find in practice**,
- Learning is a **regression ill-posed** problem.

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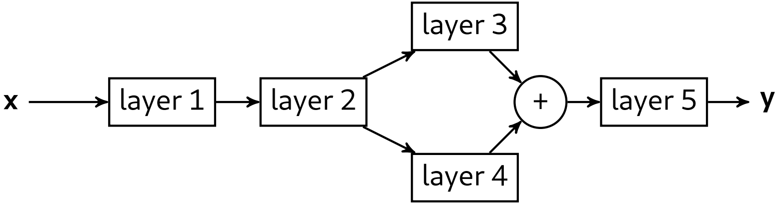
Deep learning

Main idea

- Compositional Approach: Instead of directly mapping $\mathbf{x}$ to $\mathbf{y}$, express solutions as an assembly of simple mathematical functions called **layers**
- End-to-end learning: Tune all atomic functions together
- Training: Backpropagate the gradient of the loss throughout the architecture.



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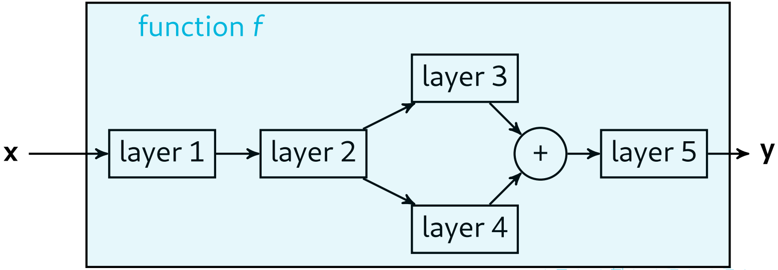

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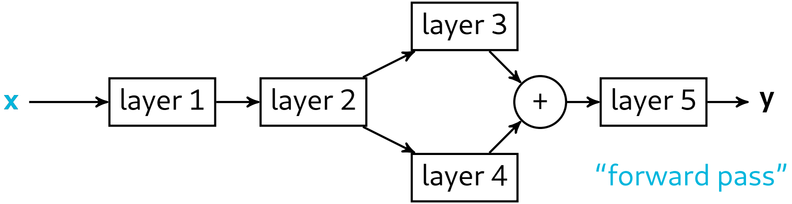

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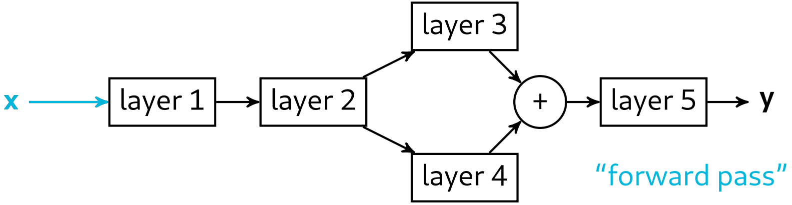

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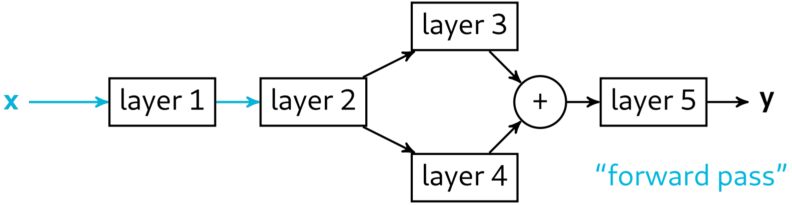

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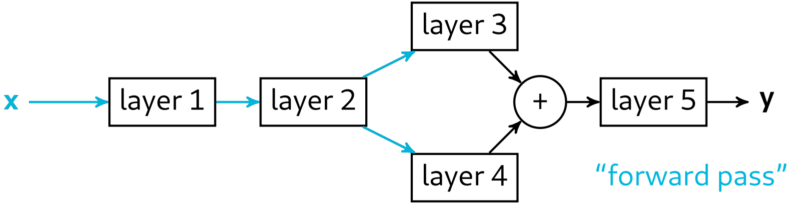

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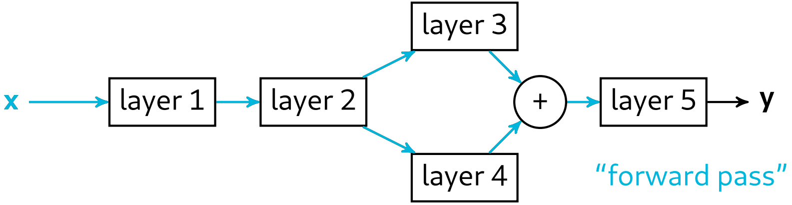

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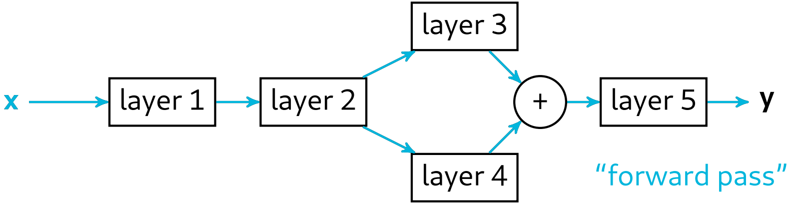

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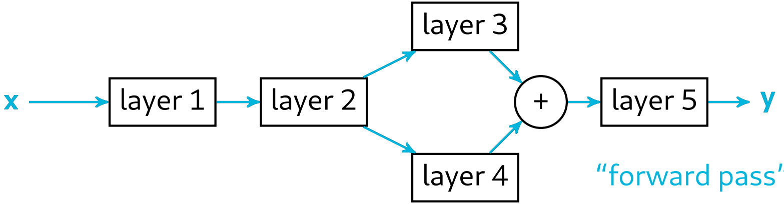

"forward pass"

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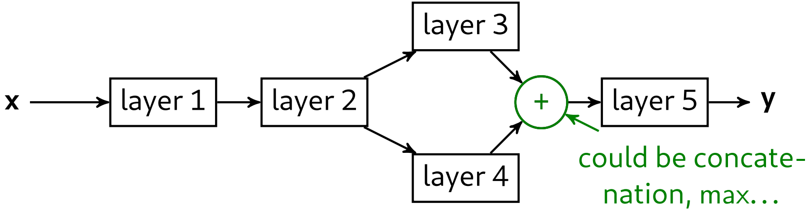

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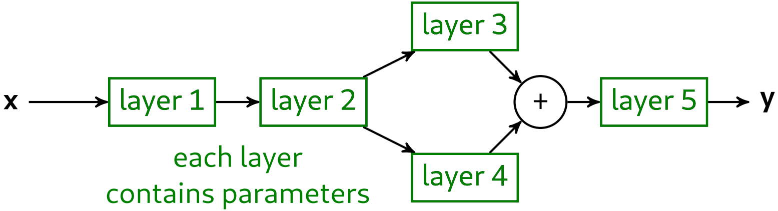

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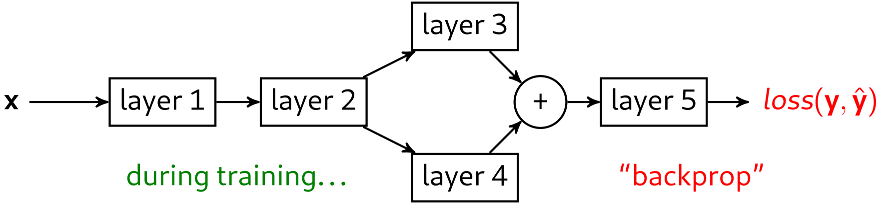

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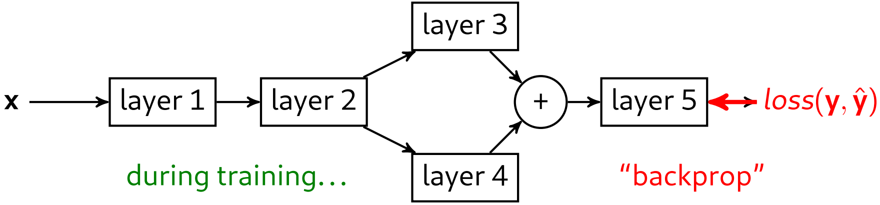

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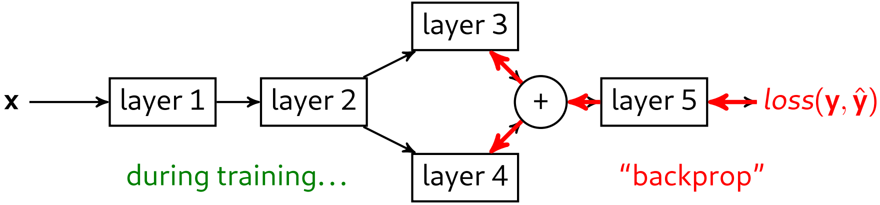

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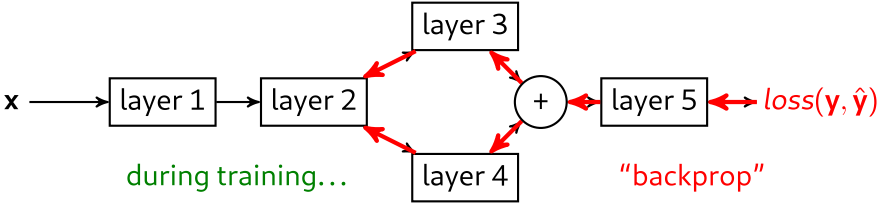

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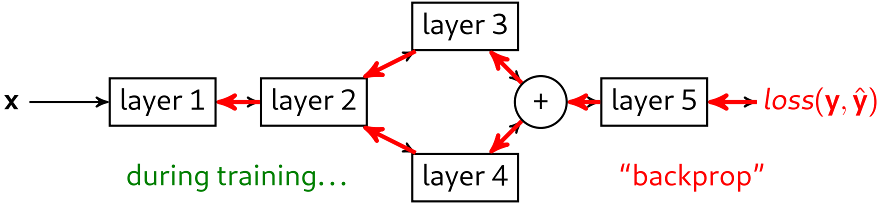

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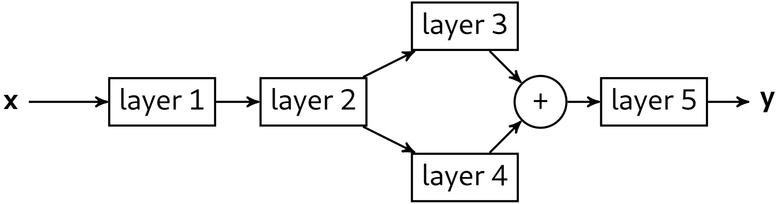


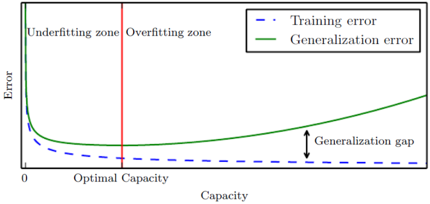
Number of layers, choice of the architecture are **hyperparameters**

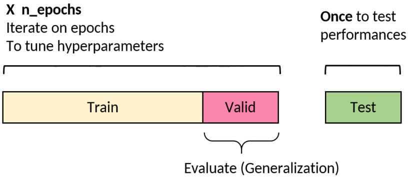
Learning Objectives

- Reduce the training error AND reduce the gap between training and **generalization error** (error on new inputs)
- Avoid **overfitting**, increase generalization for better performances on test set

Validation Set

- Examples from the training distribution NOT observed during training (e.g. 20%, 80% split) to check model generalization





Generalization vs Overfitting

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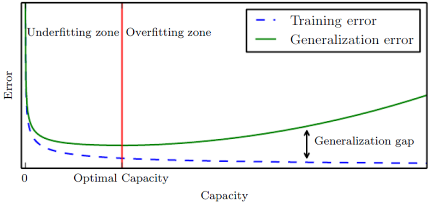

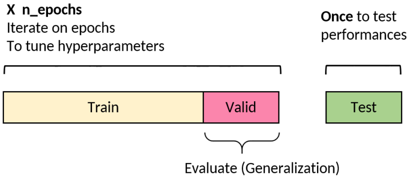

Some additional details

Layers

- $\mathbf{x} \mapsto h(\mathbf{W}\mathbf{x} + \mathbf{b})$.
  - h is a nonlinear parameterwise function (often without parameters),
  - $\mathbf{W}$ is a tensor:
    - Can be agnostic of the structure: **fully-connected layers**,
    - Can be structure-dependent: **convolutional layers**.

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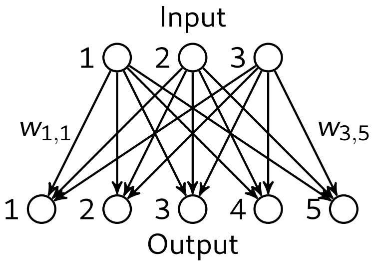
Fully connected layer



$$\begin{pmatrix} w_{1,1} & w_{1,2} & w_{1,3} & w_{1,4} & w_{1,5} \\ w_{2,1} & w_{2,2} & w_{2,3} & w_{2,4} & w_{2,5} \\ w_{3,1} & w_{3,2} & w_{3,3} & w_{3,4} & w_{3,5} \end{pmatrix}$$

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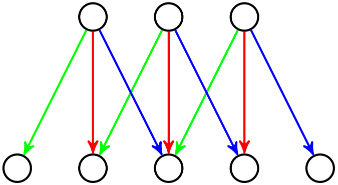
Convolutional layer



$$\begin{pmatrix} w_1 & w_2 & w_3 & 0 & 0 \\ 0 & w_1 & w_2 & w_3 & 0 \\ 0 & 0 & w_1 & w_2 & w_3 \end{pmatrix}$$

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Optimization

- Variants of the **(Stochastic) Gradient Descent (SGD)** algorithm are used:
  - Use of **moments**,
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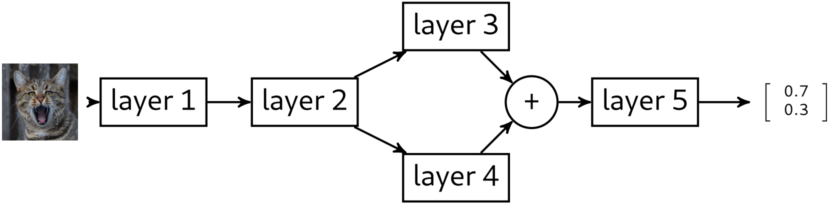
Batches

- Inputs are often treated **concurrently** using small **batches**.

The case of deep learning in classification

Inputs/outputs

- Often: inputs are **raw signals** or **feature vectors**,
- Often: outputs are vectors which **highest value** indicate the **category of the input**.



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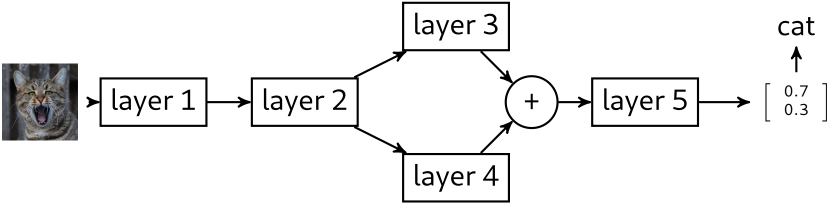

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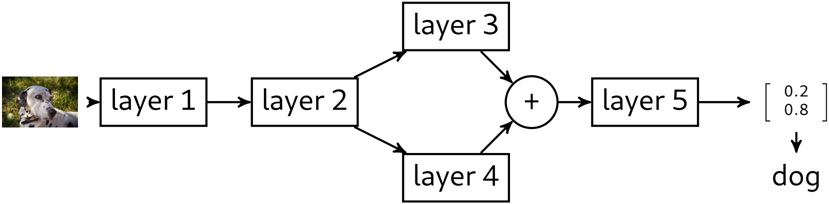

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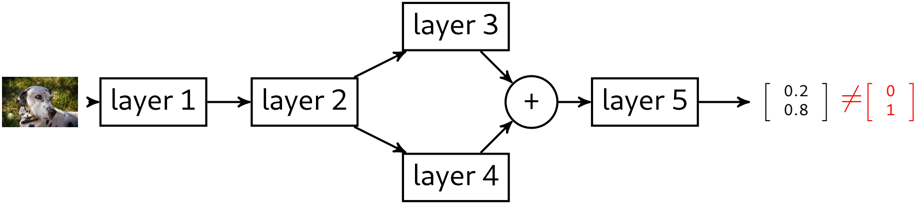

Loss and targets

- Labels are encoded as one-hot-bit vectors and called **targets**,
- Outputs are **softmaxed:** $\mathbf{y}_i \leftarrow \exp(\mathbf{y}_i)/\sum_j \exp(\mathbf{y}_j)$,
- Loss is typically **cross-entropy:** $-\log(\hat{\mathbf{y}}^\top \mathbf{y})$.

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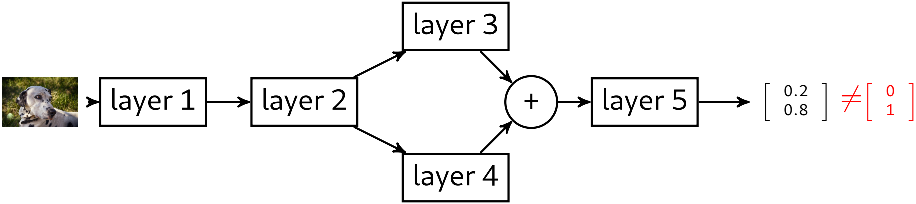

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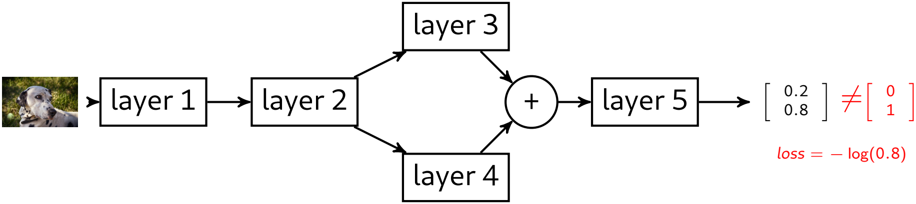

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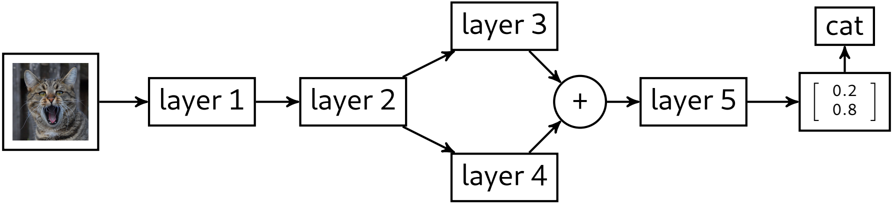
Tranfer Learning and fine-tuning

Idea: use **feature vectors** from a **backbone** (pretrained) network to train a **downstream** classifier.

Two usecases

- Fine-tuning: both the backbone and downstream networks are trained,
- Transfer Learning: Only the downstream network is trained.



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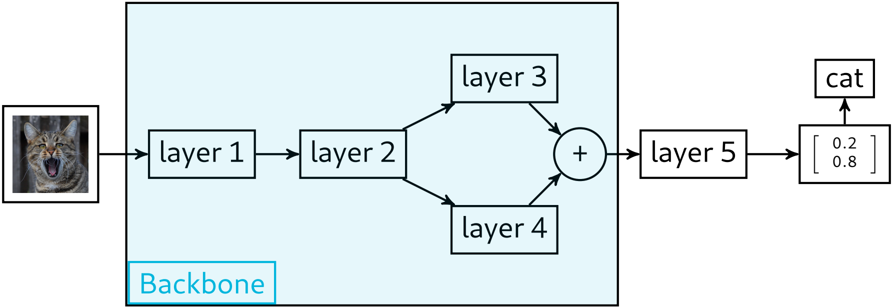

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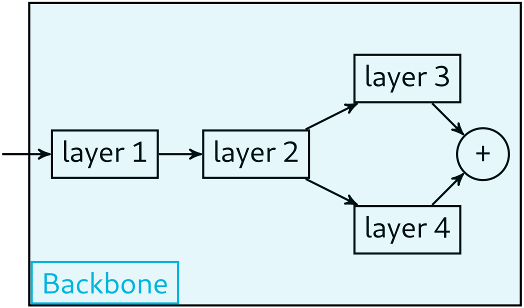

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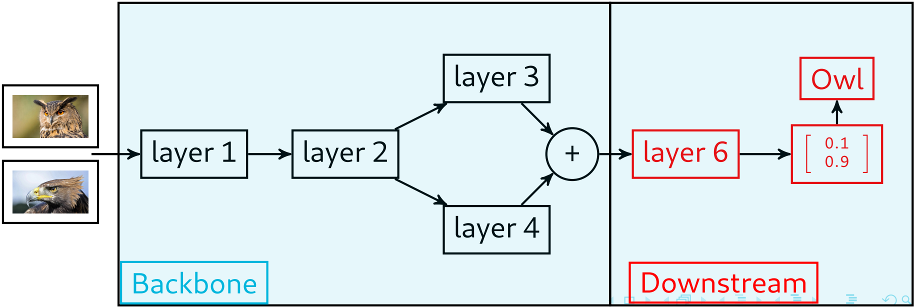

Hyperparameters

Architecture

- Number of layers
- Architecture choice (e.g. ResNet, DenseNet, VGG, ...)

Training

- Learning rate and scheduling
- Regularization (e.g. weight decay)
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Lab Session 1 and assignment

Introduction to Deep Learning

- Introduction to Deep Learning in Pytorch
- Train a full DL model from scratch
- Train a downstream model using transfer learning

Project 1 (oral presentation)

Explore one of the following architectures : ResNet, DenseNet, PreActResNet, VGG.
You have to prepare a 10 minutes (+5 min Q&A) presentation for session 2, in which you explain :

- Description of the architecture
- Hyperparameter search and results
- Study the compromise between architecture size, performance and training time.