Introduction to Deep Learning and Transfer Learning

IMT Atlantique
Bretagne-Pays de la Loire
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Course organisation

Sessions

1. Intro Deep Learning,
2. Data Augmentation and Self Supervised Learning,
3. Quantization,
4. Pruning,
5. Factorization,
6. Distillation,
7. Embedded Software and Hardware for DL,
8. Presentations for challenge.

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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 $\mathcal{L}$: 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

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

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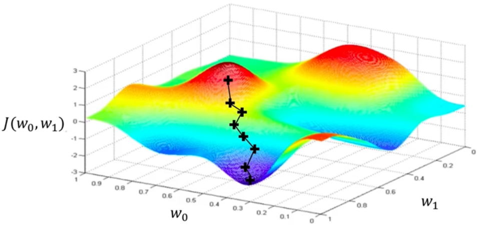
- Loss: $J(\mathbf{W}) = \sum_i \mathcal{L}(f(\mathbf{x}^{(i)}, \mathbf{W}), \mathbf{y}^{(i)}), i = examples$
- Model parameters: $\mathbf{W}^* = argmin(J(\mathbf{W}))$

Training Algorithm

- Randomly Initialize model weights
- Compute Gradient of the Loss $\frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
- Update weights $\mathbf{W} \leftarrow \mathbf{W} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
- Repeat until convergence

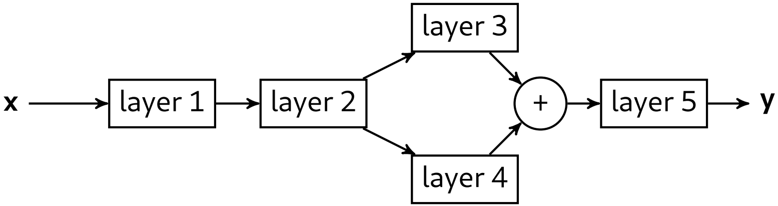


from MIT course `introtodeeplearning.com`

Deep learning

Main idea

- Compositional Approach: Instead of directly mapping **x** to **y**, express solutions as an assembly of simple mathematical functions called **layers**
- End-to-end learning: Tune all atomic functions together
- Training: Backpropagate throughout the architecture (to compute the gradient of the loss wrt all layers parameters)



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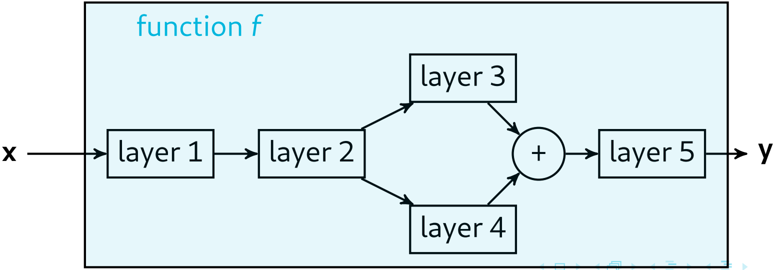

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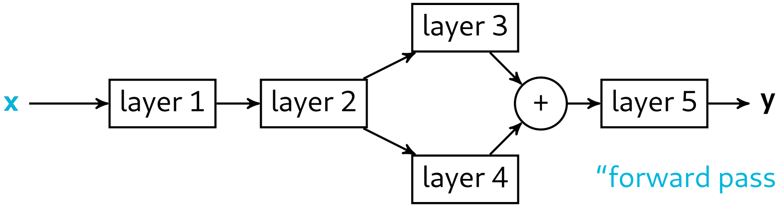

"forward pass"

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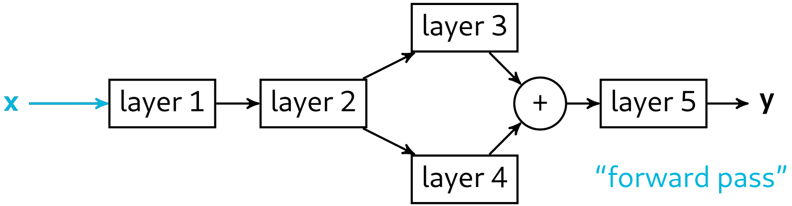

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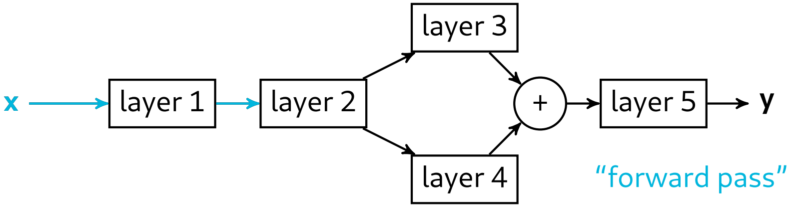

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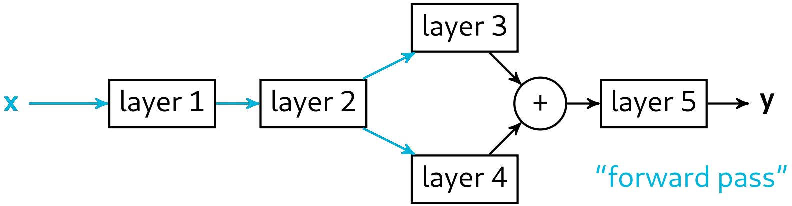

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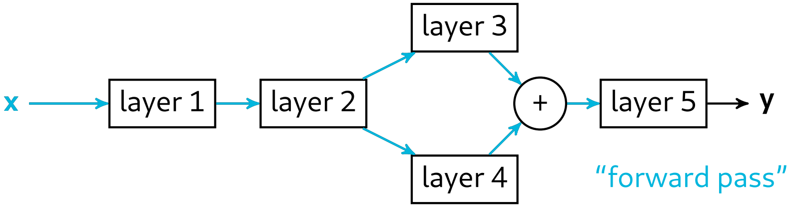

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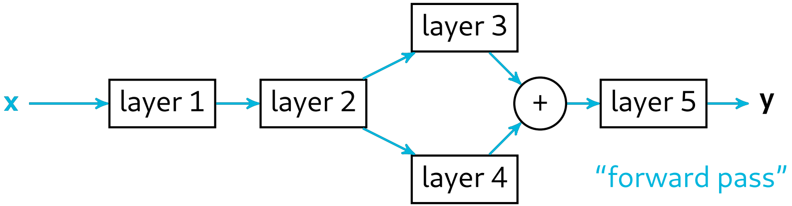

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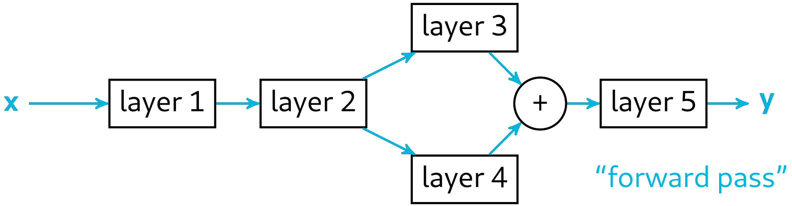

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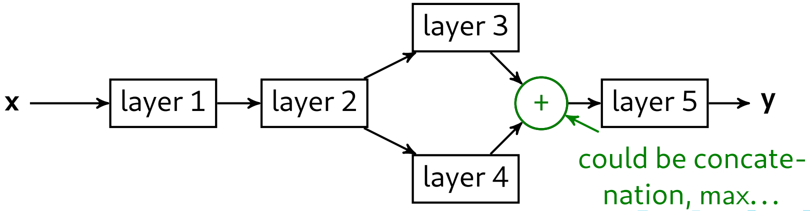

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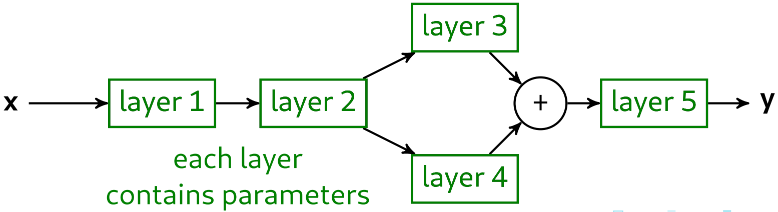

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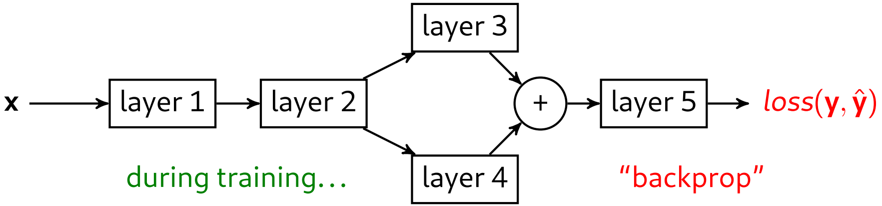

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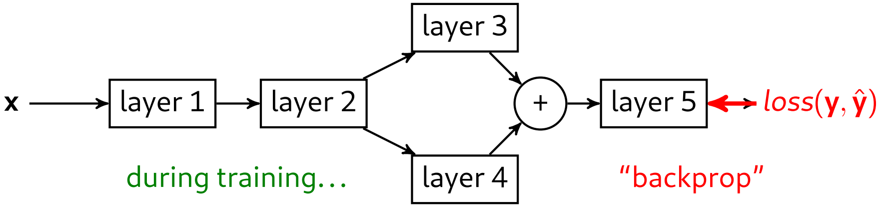

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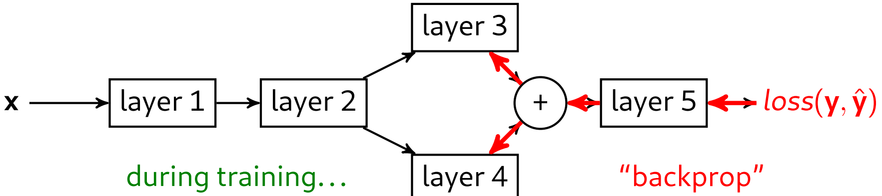

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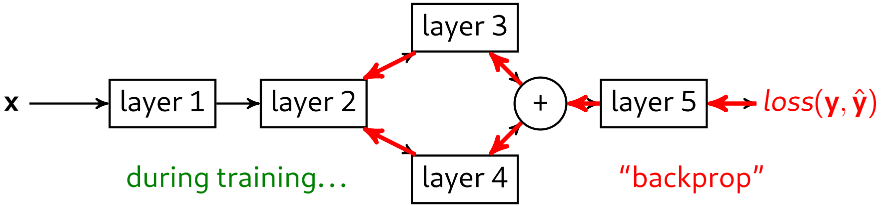

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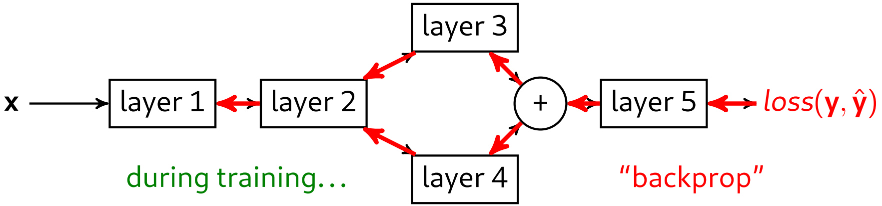

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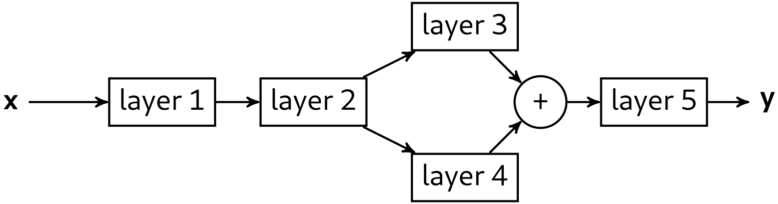

Number of layers, choice of the architecture are **hyperparameters**

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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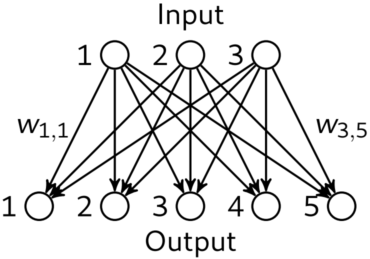
Fully connected layer



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

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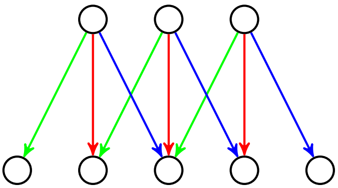
Convolutional layer



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

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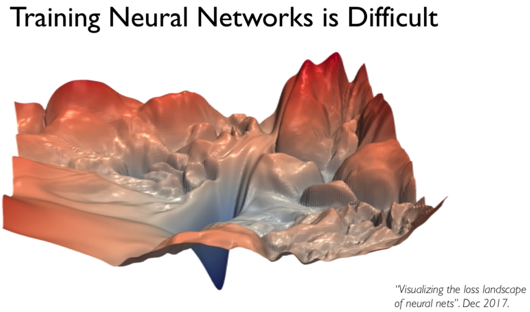
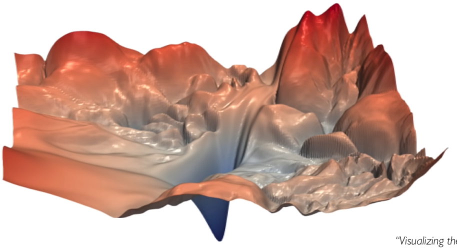


Optimization with Differentiable Algorithmic

- Learning rate η : $\mathbf{W} \leftarrow \mathbf{W} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{W}}$
- Variants of the **Stochastic Gradient Descent (SGD)** algorithm are used:
  - Use of **moments**,
  - Use of **regularizers**.

Some additional details



"Visualizing the loss landscape of neural nets". Dec 2017.

Batches

- To accelerate computations, inputs are often treated **concurrently** using small **batches**.

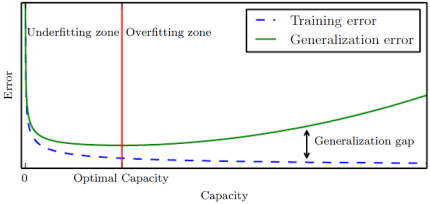
Generalization vs Overfitting

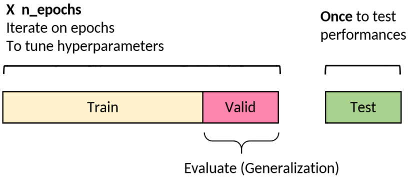
Learning Objectives

- 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





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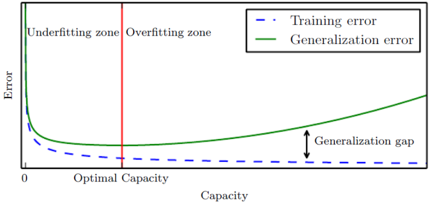
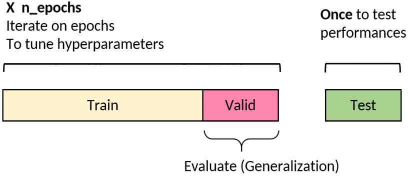
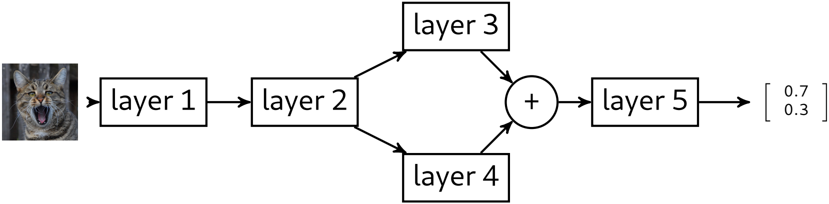




The case of deep learning in classification

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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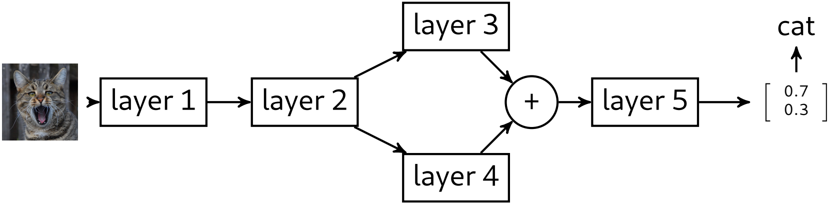

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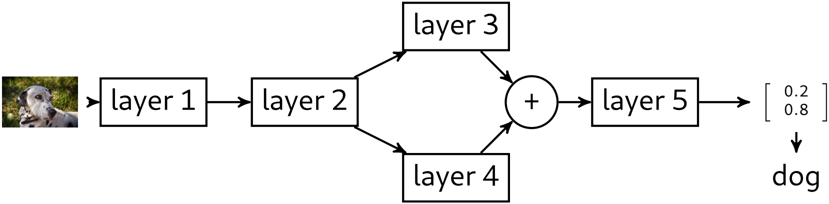

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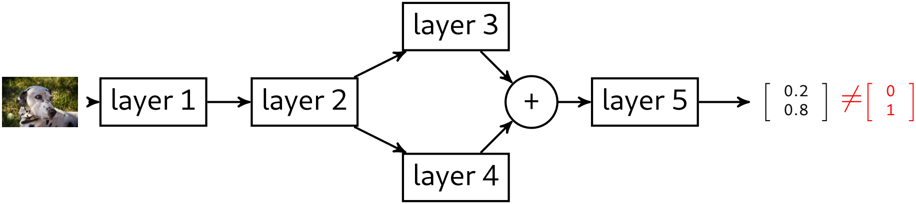

Loss and targets

- 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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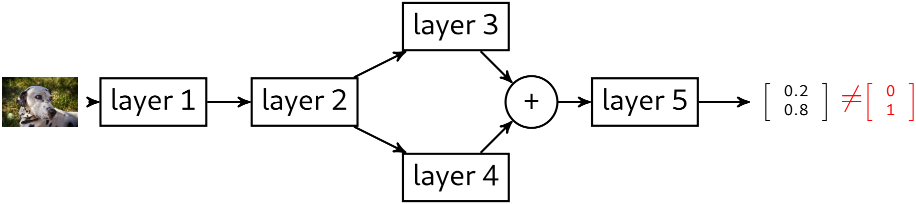

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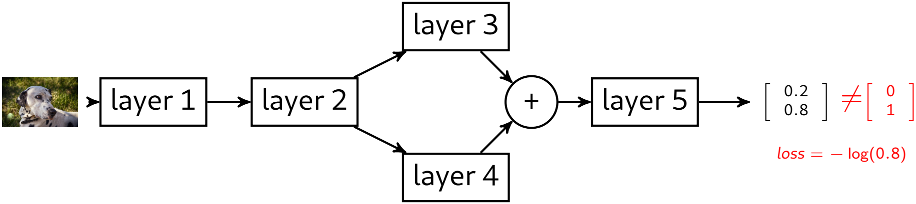

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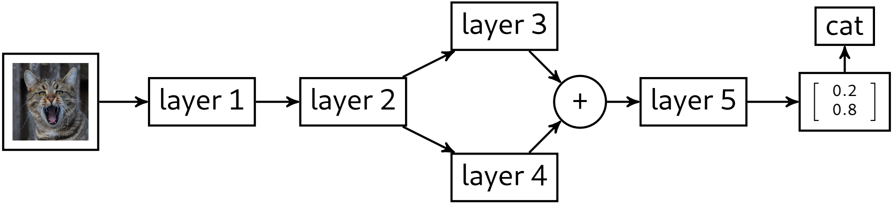
Tranfer Learning and fine-tuning

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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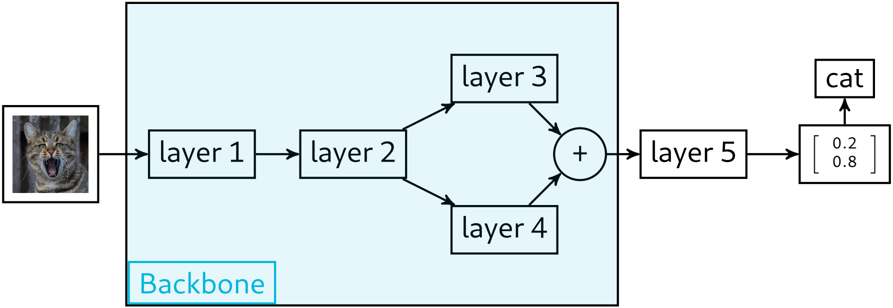

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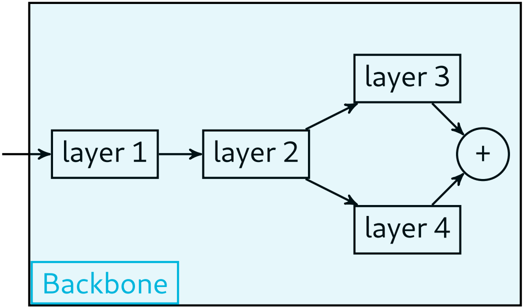

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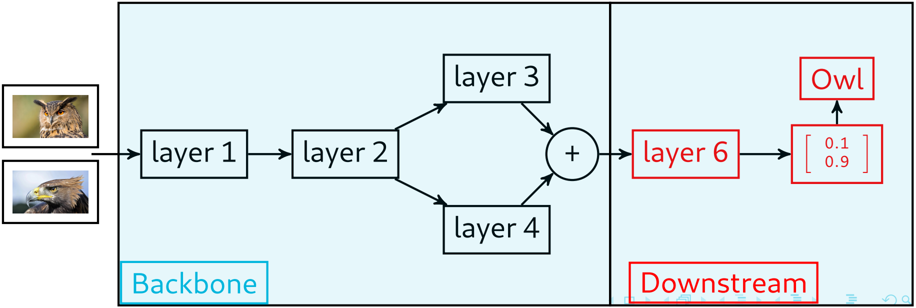

Hyperparameters

Architecture

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

Training

- Learning rate and scheduling
- Regularization (e.g. weight decay)
- Choice of optimizer (e.g. SGD)

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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 3, in which you explain :

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