Introduction to Deep Learning

Bootcamp IID 2021

Frédérik Paradis

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3 mai 2021

Who Am I?

Frédérik Paradis

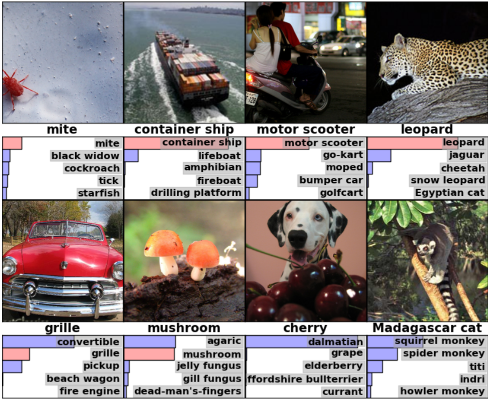
Lead developer of Poutyne

Ph.D. Student at Université Laval

Applied AI Consultant and Researcher at Baseline

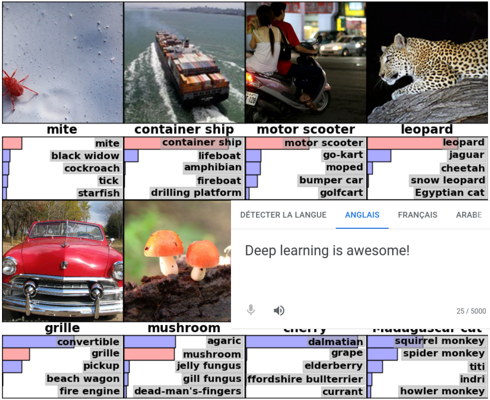
frederik-paradis

Deep Neural Networks



[Krizhevsky et al. 2012, "ImageNet Classification with Deep Convolutional Neural Networks"]

Deep Neural Networks



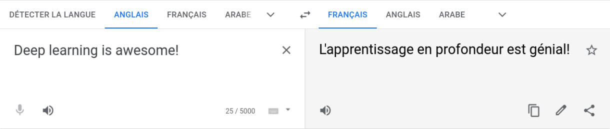


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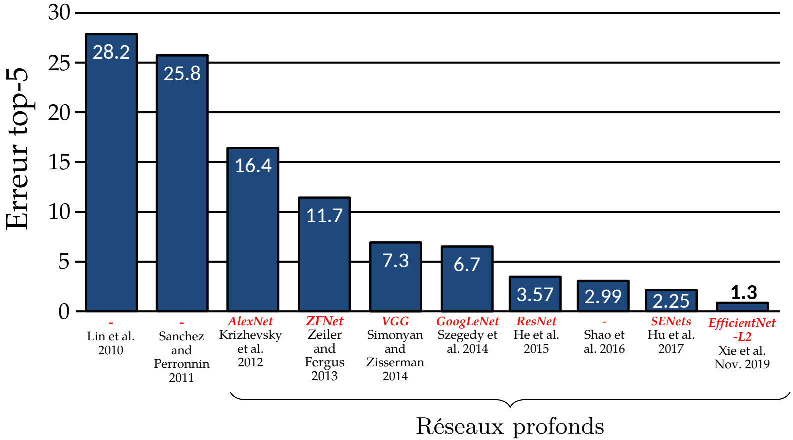
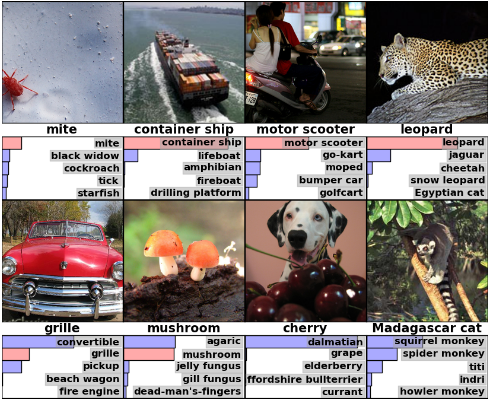
Image classification challenge on the 1,000 image classes of ImageNet



http://www2.ift.ulaval.ca/~pgiguere/cours/DeepLearning/2020/01-Introduction-2020.pdf

- Object classification



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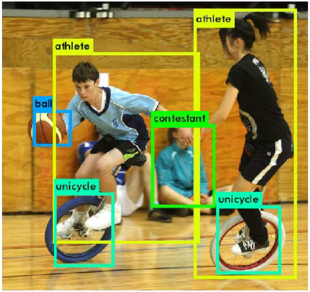
Computer Vision

- Object classification
- Object detection



[Redmon and Farhadi 2017, "YOLO9000: better, faster, stronger"]

Computer Vision

- Object classification
- Object detection
- Image segmentation

[Cordts et al. 2016, "The cityscapes dataset for semantic urban scene understanding"]

Computer Vision

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- Object detection
- Image segmentation
- Image matching (e.g. facial recognition)

[Jesorsky et al. 2001, "Robust face detection using the hausdorff distance"]

Computer Vision

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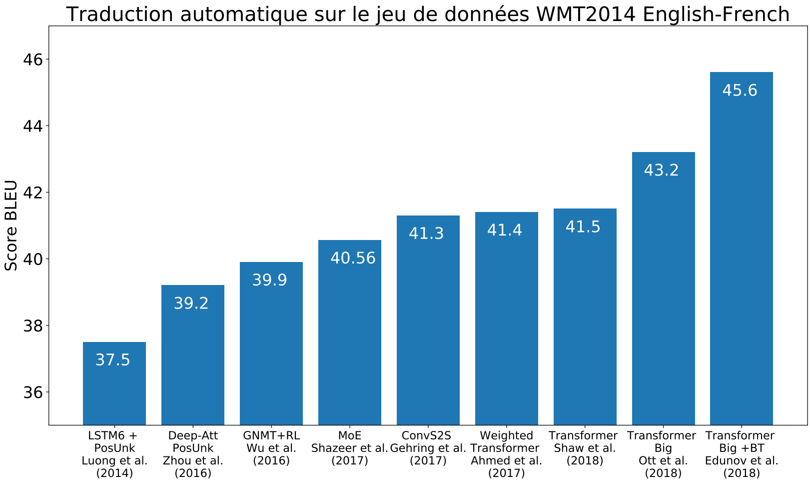
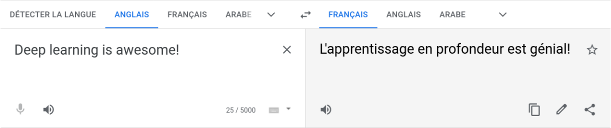
Natural Language Processing (NLP)



https://paperswithcode.com/sota/machine-translation-on-wmt2014-english-french

Natural Language Processing

- Translation



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- Translation
- Text classification (e.g. topic, sentiment)

Natural Language Processing

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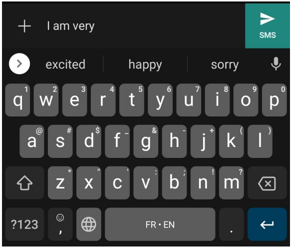

Natural Language Processing

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- etc.

Dataset $\{(x^{(1)}, y^{(1)}), \ldots, (x^{(m)}, y^{(m)})\}$

Machine Learning

Dataset $\{(x^{(1)}, y^{(1)}), \ldots, (x^{(m)}, y^{(m)})\}$

$\downarrow$

Learning algorithm

Dataset $\{(x^{(1)}, y^{(1)}), \ldots, (x^{(m)}, y^{(m)})\}$

$\downarrow$

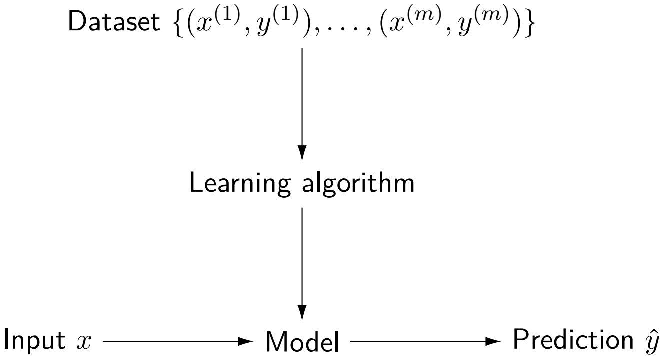
Learning algorithm

$\downarrow$

Model

Machine Learning

$$
\begin{tikzcd}
& \text{Dataset } \{(x^{(1)}, y^{(1)}), \ldots, (x^{(m)}, y^{(m)})\} \arrow[d] \\
& \text{Learning algorithm} \arrow[d] \\
\text{Input } x \arrow[r] & \text{Model}
\end{tikzcd}
$$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Learning algorithm
Input x
Model
Prediction $\hat{y}$

The Basis of Neural Networks: The Neuron

Let $x = (x_1, x_2, \ldots, x_n)$ be n features (or variables in statistics).

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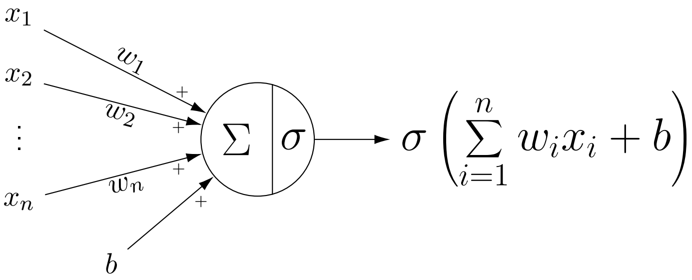
A neuron computes the following.



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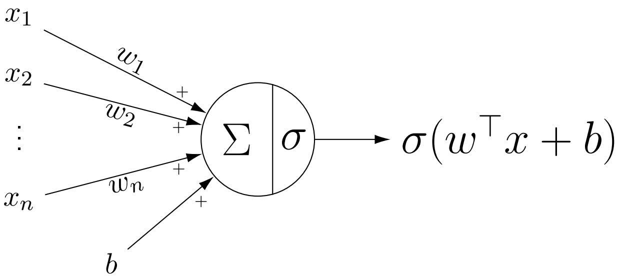

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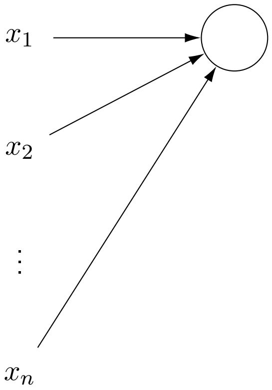
Neural Network



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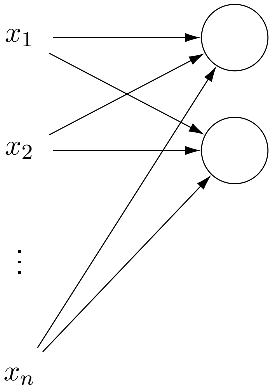

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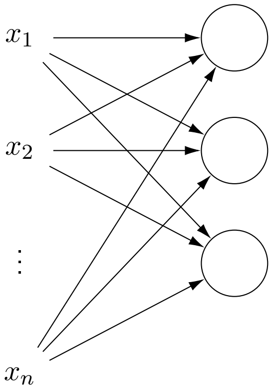

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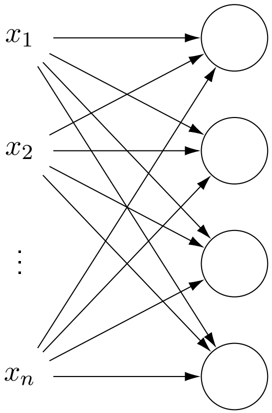

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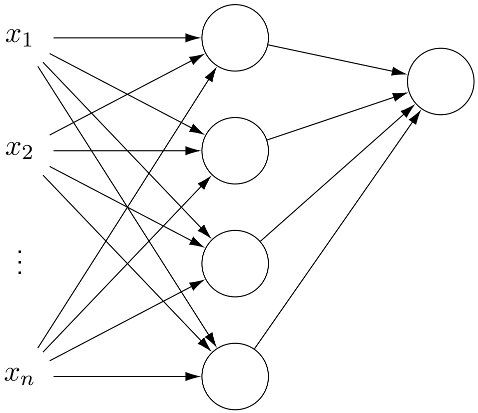

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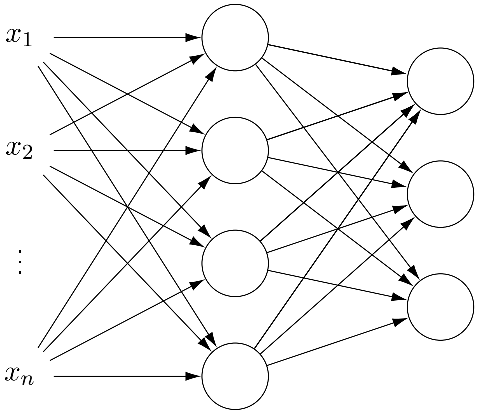

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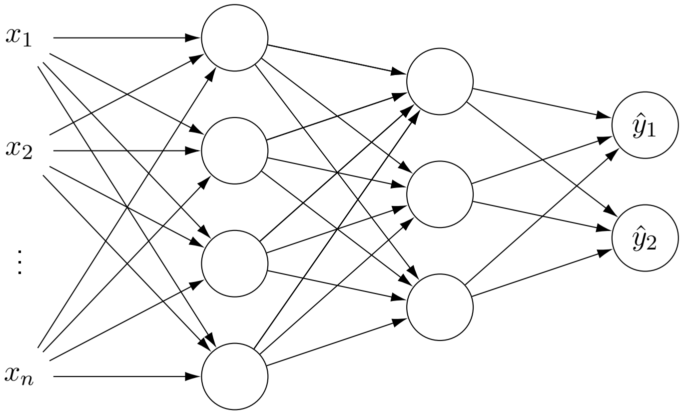

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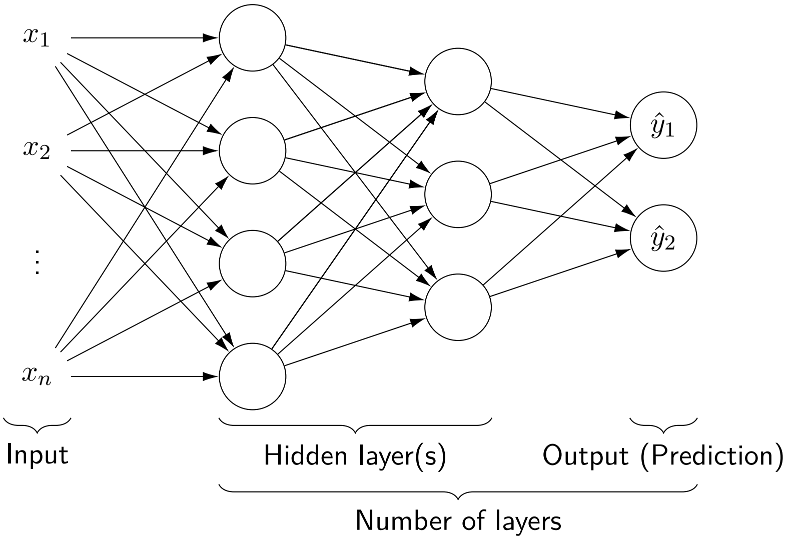

Activation Functions

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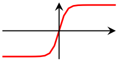
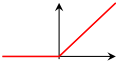


- The ReLU function:

$$\mathsf{ReLU}(z) = \max(0, z)$$



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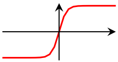

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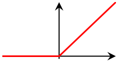
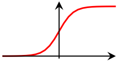


- The logistic function (also called sigmoid function):

$$\sigma(z) = \frac{1}{1 + \exp(-z)}$$



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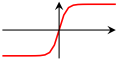

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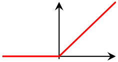

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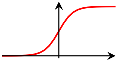

- The softmax function:

$$\text{softmax}\,(z)_i = \frac{\exp(z_i)}{\sum_{j=1}^{m} \exp(z_j)}$$

for $z = Wx + b \in \mathbb{R}^m$.

Loss Function

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- Cross-entropy loss for classification with C classes ($\mathcal{Y} = \{1, \ldots, C\}$)
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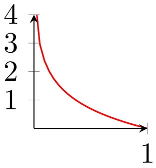

Regularization

To avoid overfitting (i.e. learning the training examples by heart), we may add a penalty term to the loss[1]:

$$\mathcal{L}(f(x), y) = \mathcal{L}_{\mathsf{MLE}}(f(x), y) + \lambda\Omega(f)$$

[1] MLE stands for Maximum Likehood Estimation.

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Goal: minimize the loss function for all examples (pairs (x, y))!

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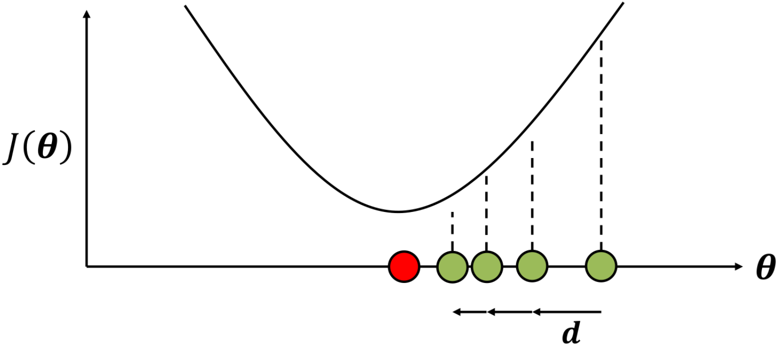
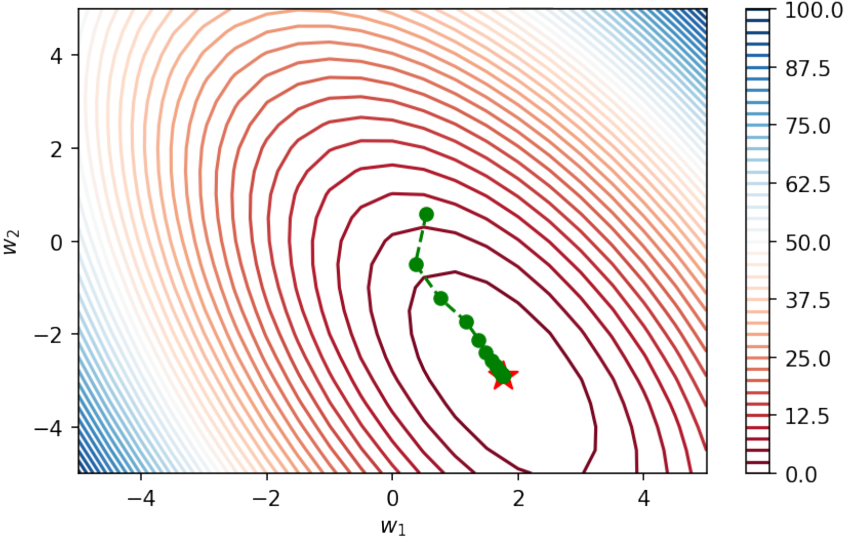
$$
\begin{aligned}
J(\theta) &= \mathop{\mathbb{E}}_{(x,y)\in\mathcal{D}} \mathcal{L}(f(x;\theta), y) \\
&\approx \frac{1}{N}\sum_{i=1}^{N} \mathcal{L}(f(x_i;\theta), y_i)
\end{aligned}
$$

Gradient Descent



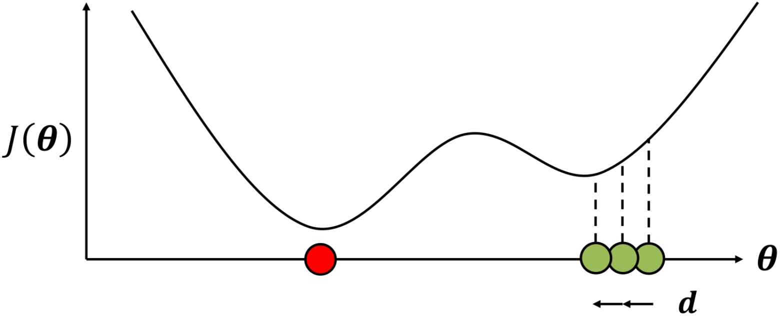
From Université Laval GLO-7030 by Ludovic Trottier

Gradient Descent



From Université Laval GLO-7030 by Pascal Germain

Gradient Descent For Deep Neural Networks



From Université Laval GLO-7030 by Ludovic Trottier

Gradient Descent For Deep Neural Networks

Adapted by Philippe Giguère for Université Laval GLO-7030 from Standford CS231N

Réalité : trouver le fond de la vallée embrumée, à tâtons

Computation of Gradient

Using **"backpropagation"**, we compute the **partial derivative** of each parameter **with respect to the loss**. The vector containing all partial derivatives is called the **gradient**.

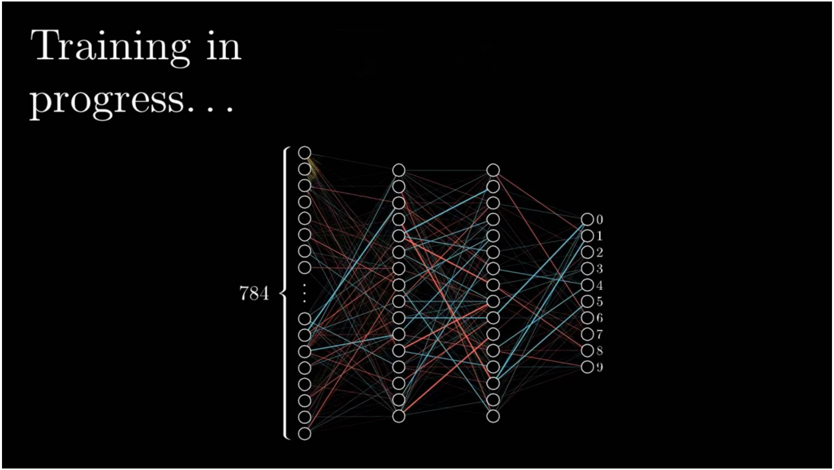
$$d = \nabla_\theta J(\theta) = \left[\frac{\partial J(\theta)}{\partial \theta_1}, \ldots, \frac{\partial J(\theta)}{\partial \theta_n}\right]$$

To update the parameters:

$$\theta \leftarrow \theta - \epsilon d$$

ϵ is called the learning rate.

Gradient



Extrait de `https://youtu.be/IHZwWFHWa-w` 3Blue1Brown

Optimization Algorithms

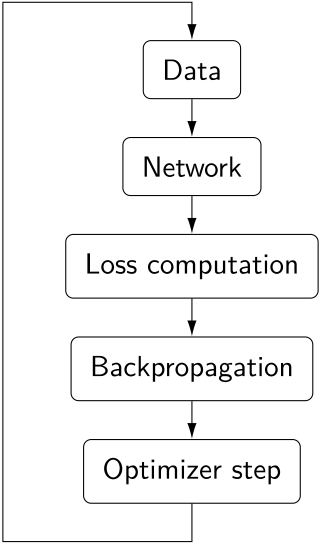
Simplest update rule:

$$\theta \leftarrow \theta - \epsilon d$$

Many types exist:

- **SGD**
- SGD with momentum
- SGD with momentum Nesterov
- Adagrad
- RMSprop
- **Adam**

Training Procedure



Training Procedure

procedure $\textsc{Train}(f(\cdot;\theta),\ S)$

input: Neural network f parameterized by θ

input: Dataset $S = \{(x_1, y_1), \ldots, (x_N, y_N)\}$

end procedure

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  for n epochs **do**

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  for n epochs **do**

    Let $S' = S$

    while $S' \neq \emptyset$ **do**

      Draw a batch $B \subseteq S'$ of b examples without replacement in S'.

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      $d = \nabla_\theta \ell$
      Update θ with d using chosen optimizer
(e.g. $\theta \leftarrow \theta - \epsilon d$).
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end procedure

Deep Learning Libraries

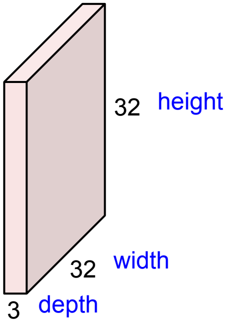
Deep Learning Libraries

TensorFlow

PyTorch

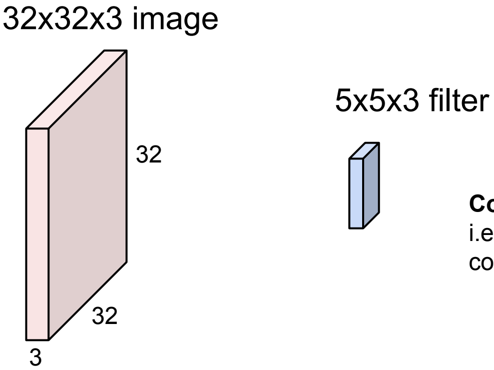
PyTorch Demo

Convolution Layer



Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



Convolve the filter with the image i.e. "slide over the image spatially, computing dot products"

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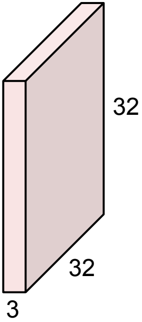
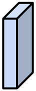
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image



5x5x3 filter



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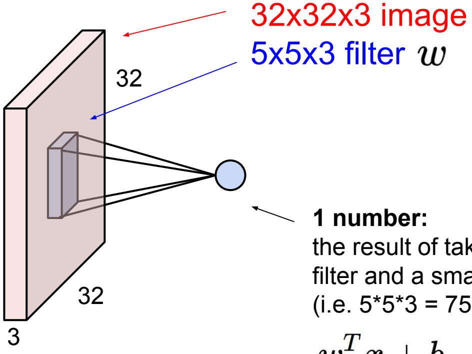
Convolution Layer

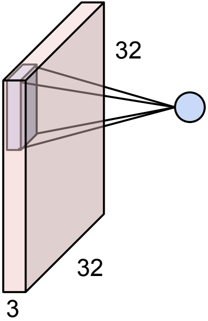


1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

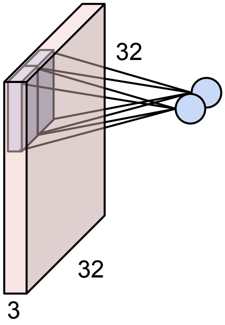
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



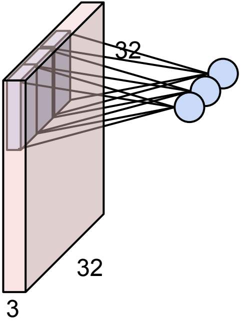
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



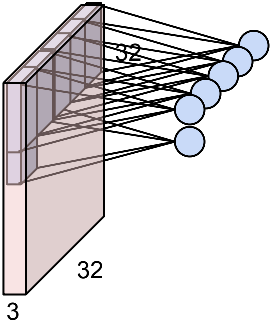
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



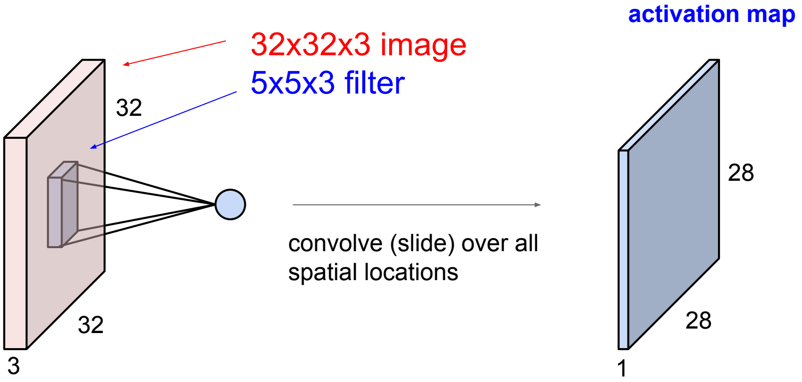
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



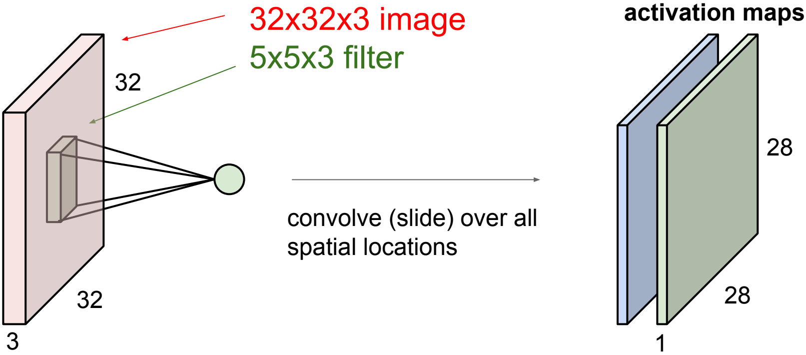
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



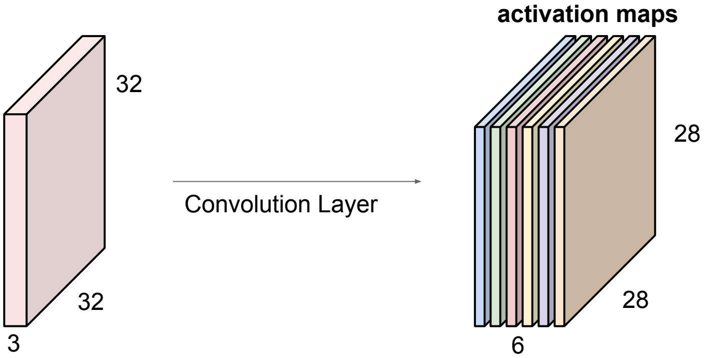
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



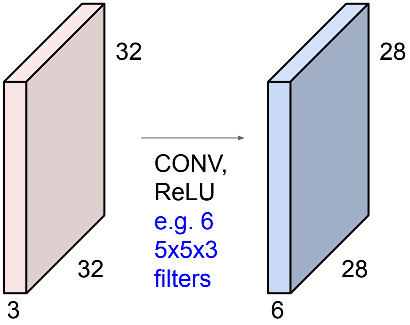
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



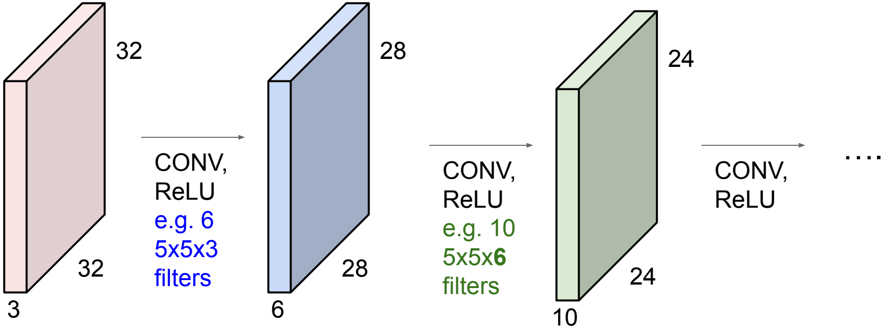
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



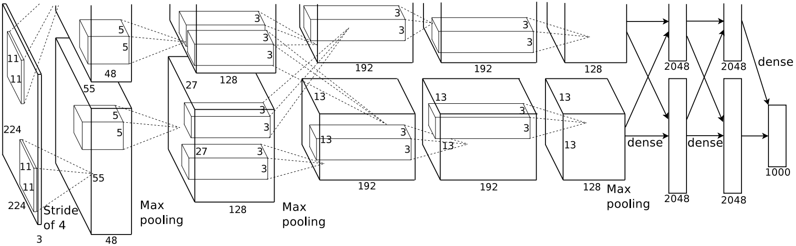
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Other Types of Layers

Many types of layers exist. Here is a few.

- Max pooling/averge pooling
- Batch normalization
- Dropout

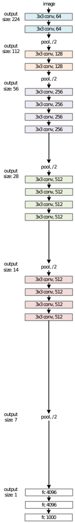
Deep Neural Network Architectures



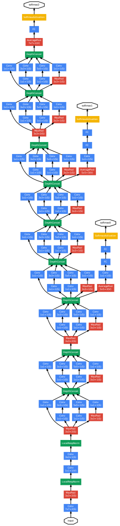
AlexNet

[Krizhevsky et al. 2012, “ImageNet Classification with Deep Convolutional Neural Networks”]

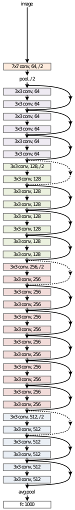
Deep Neural Network Architectures



VGG



GoogLeNet (or Inception)



ResNet

[Simonyan and Zisserman 2014, “Very deep convolutional networks for large-scale image recognition”]
[Szegedy et al. 2015, “Going deeper with convolutions”]
[He et al. 2016, “Deep residual learning for image recognition”]

Demo

Liens de référence

- Cours GLO-4030/7030 Apprentissage par réseaux de neurones profonds:
  - Slides: https://ulaval-damas.github.io/glo4030/
  - Laboratoire: https://github.com/ulaval-damas/glo4030-labs
- Vidéos du cours CS231n: https://www.youtube.com/watch?v=vT1JzLTH4G4&list=PLC1qU-LWwrF64f4QKQT-Vg5Wr4qEE1Zxk
- Tutoriels et documentation de PyTorch
  - https://pytorch.org/tutorials/ (pas tout le temps les meilleures pratiques)
  - https://pytorch.org/docs/stable/index.html
- Documentation de Poutyne: https://poutyne.org/

The End.

Questions?

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He, Kaiming et al. (2016). "Deep residual learning for image recognition". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770–778.

Jesorsky, Oliver, Klaus J Kirchberg, and Robert W Frischholz (2001). "Robust face detection using the hausdorff distance". In: *International conference on audio-and video-based biometric person authentication*. Springer, pp. 90–95.

Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton (2012). "ImageNet Classification with Deep Convolutional Neural Networks". In: *NIPS*.

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- Szegedy, Christian et al. (2015). "Going deeper with convolutions". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1–9.