

# Introduction to Deep Learning

## Bootcamp IID 2021

Frédérik Paradis

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3 mai 2021



UNIVERSITÉ  
**LAVAL**

**1** Who Am I?

**2** Introduction

**3** Neural Networks

**4** Training

**5** Convolutional Networks

## 1 Who Am I?

## 2 Introduction

## 3 Neural Networks

## 4 Training

## 5 Convolutional Networks

# Who Am I?



## Frédérik Paradis

🔥 Lead developer of Poutyne

Ḍ Ph.D. Student at Université Laval

B Applied AI Consultant and  
Researcher at Baseline

[in frederik-paradis](#)

**1** Who Am I?

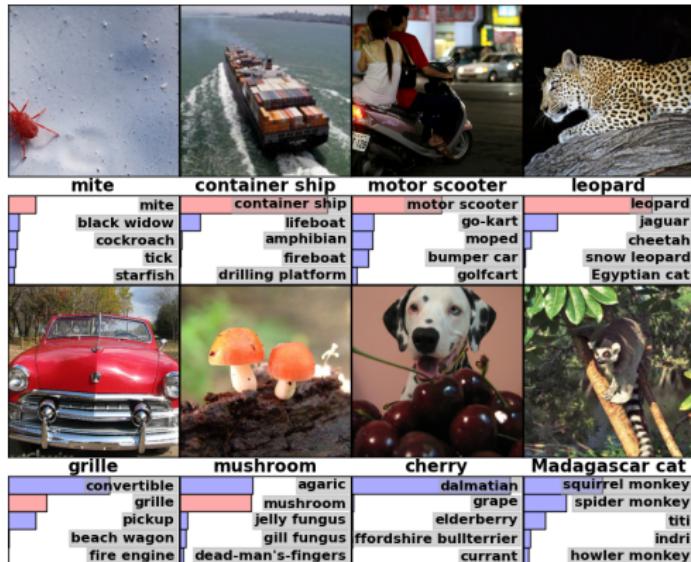
**2** Introduction

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# Deep Neural Networks



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

# Deep Neural Networks

The image shows a user interface for a deep learning model. At the top, there are four small images with their predicted labels below them:

- A red mite: mite, black widow, cockroach, tick, starfish
- A container ship: container ship, lifeboat, amphibian, fireboat, drilling platform
- A motor scooter: motor scooter, go-kart, moped, bumper car, golfcart
- A leopard: leopard, jaguar, cheetah, snow leopard, Egyptian cat

Below these are two more images with labels:

- A red classic car: grille, convertible, grille, pickup, beach wagon, fire engine
- Two orange mushrooms: mushroom, agaric, mushroom, jelly fungus, gill fungus, dead-man's-fingers

At the bottom, there is a text input field with the placeholder "Deep learning is awesome!" and a translation section:

DÉTECTOR LA LANGUE ANGLAIS FRANÇAIS ARABE ▾ FRANÇAIS ANGLAIS ARABE ▾

Deep learning is awesome! × L'apprentissage en profondeur est génial! ☆

25 / 5000

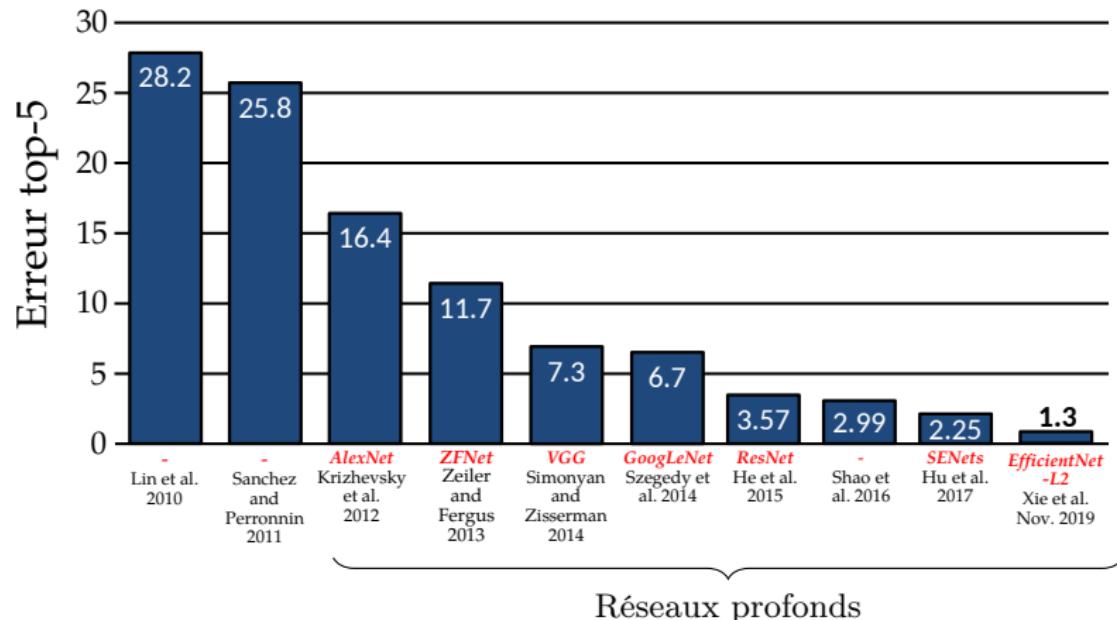
grille, convertible, agaric, dalmatian, squirrel monkey, grape, spider monkey, elderberry, titi, ffordshire bullterrier, currant, howler monkey, indri

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

# Computer Vision

## Large Scale Visual Recognition Challenge (LSVRC)

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



# Computer Vision

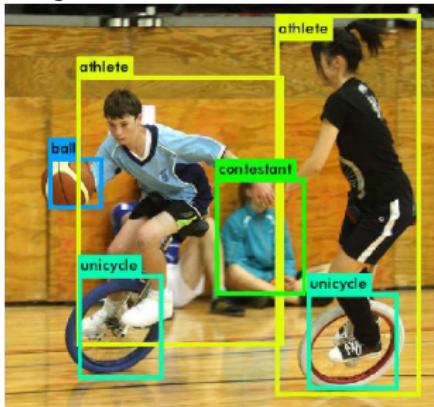
## Object classification



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

# 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

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

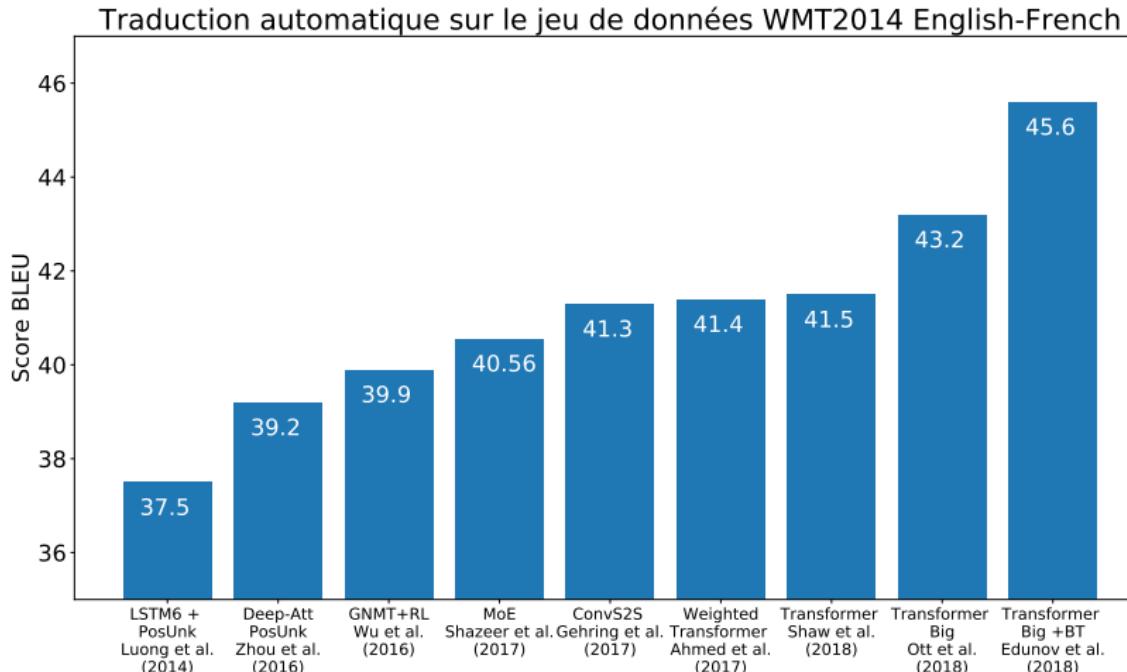


[Jesorsky et al. 2001, "Robust face detection using the hausdorff distance"]

# Computer Vision

- Object classification
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- Image segmentation
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- etc.

# Natural Language Processing (NLP)



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

# Natural Language Processing

## ■ Translation

The screenshot shows a translation interface with two main sections. The left section is for input, containing the English sentence "Deep learning is awesome!". The right section is for output, displaying the French translation "L'apprentissage en profondeur est génial!" along with a single star icon. Both sections include small audio icons and edit/copy/share buttons at the bottom. Above the input section, there's a header with language detection and selection buttons: "DÉTECTOR LA LANGUE", "ANGLAIS" (which is underlined), "FRANÇAIS", and "ARABE". Below the input, there are progress indicators showing "25 / 5000" and a zoom level icon.

# Natural Language Processing

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



John Doe

★★★★★ **Awesome product**

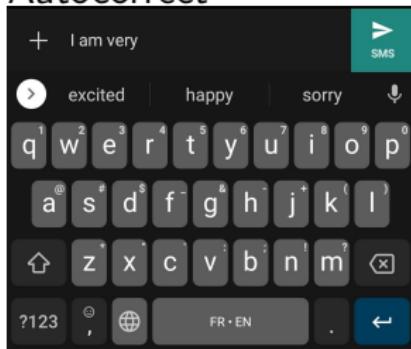
Reviewed in Canada on May 04, 2021

This is an awesome product. It couldn't be better!!!

16 people found this helpful

# Natural Language Processing

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



# Natural Language Processing

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

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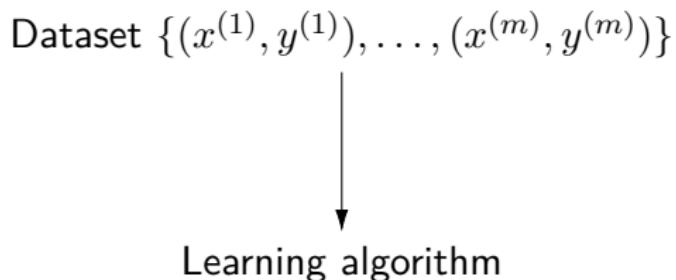
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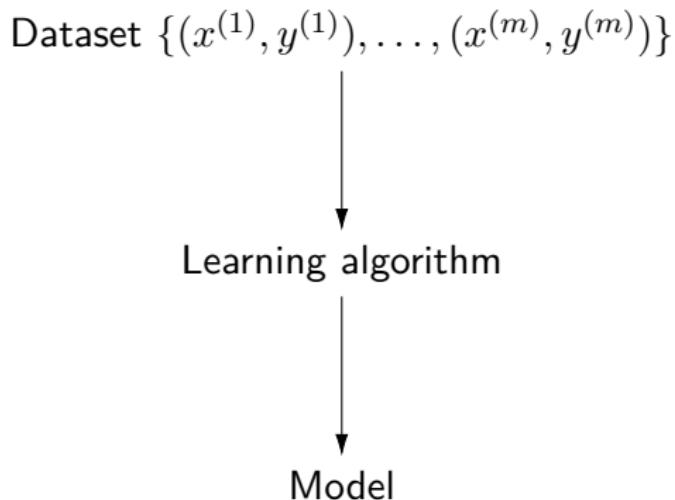
# Machine Learning

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

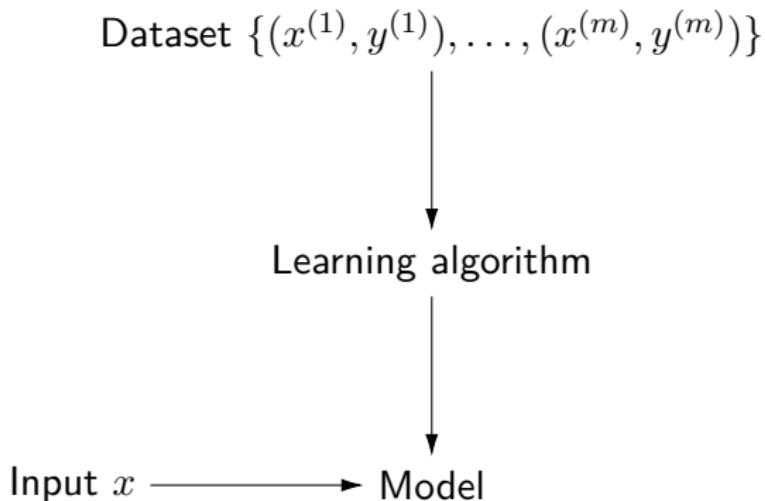
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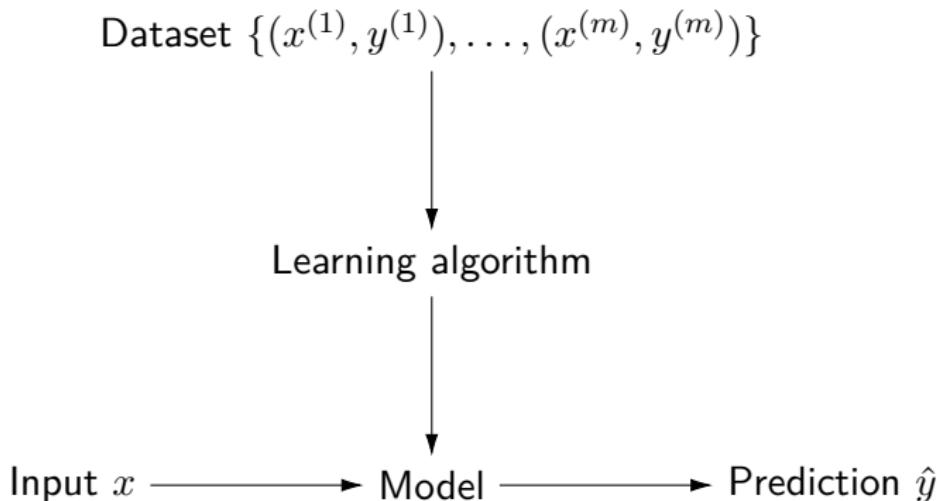
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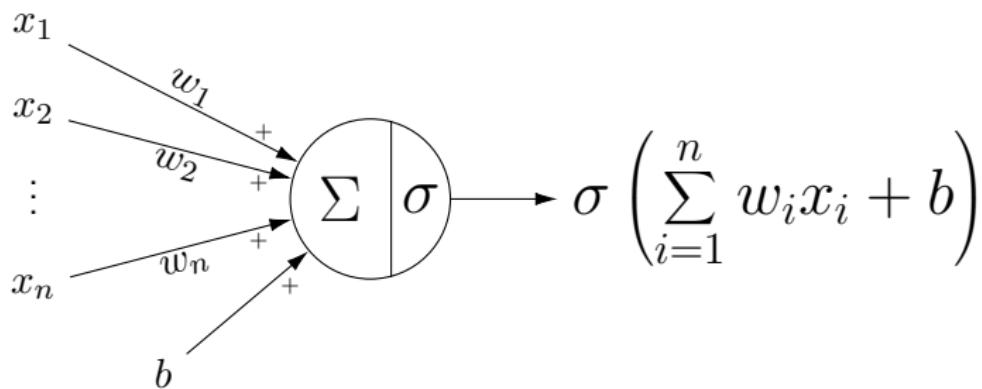


# The Basis of Neural Networks: The Neuron

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

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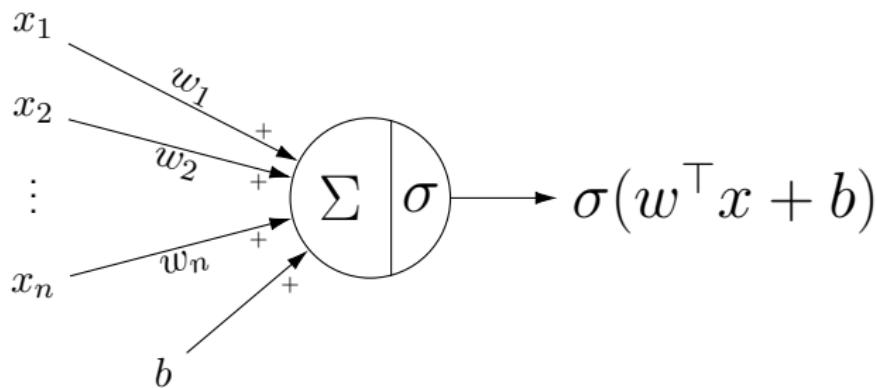
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where  $w$  are called the weights of the neuron and  $\sigma(\cdot)$  is a non-linear activation function.

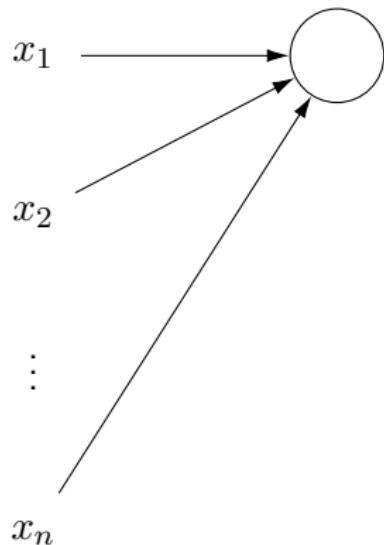
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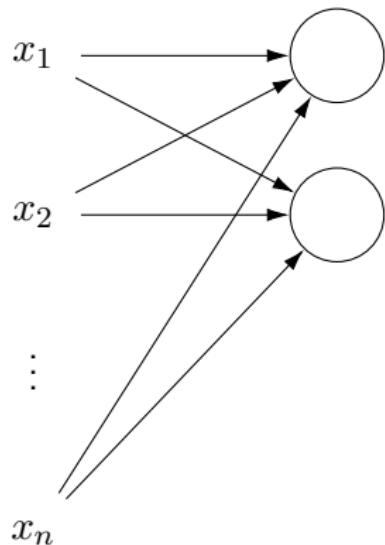


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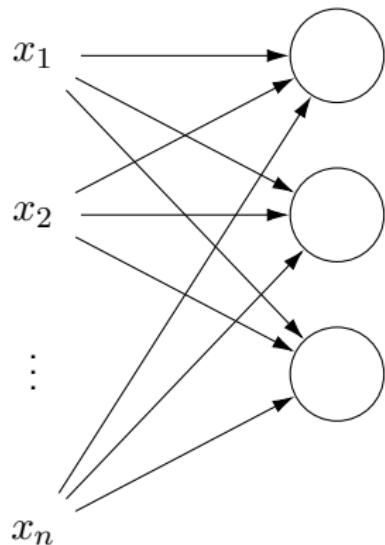
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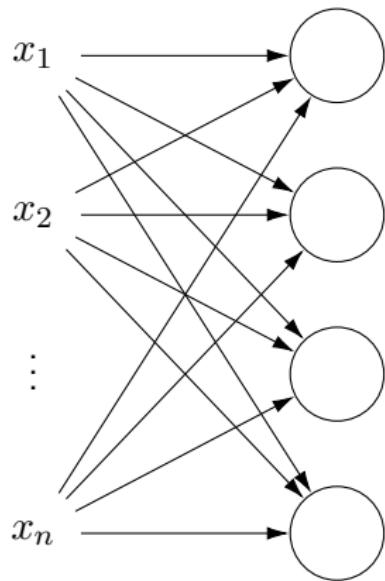
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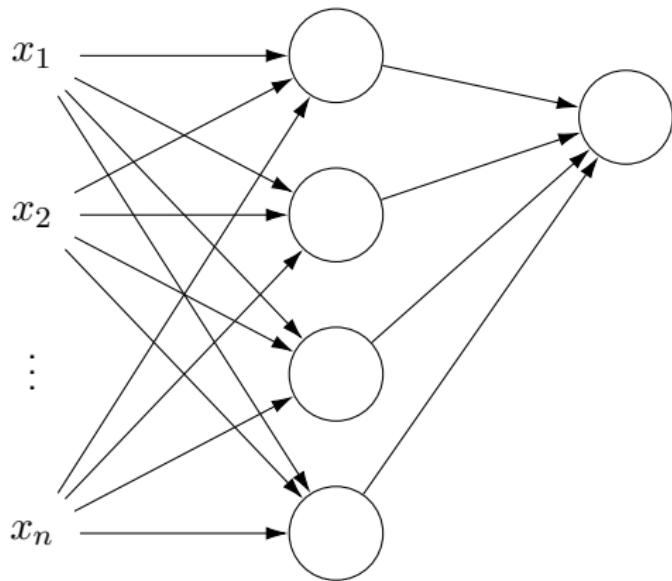
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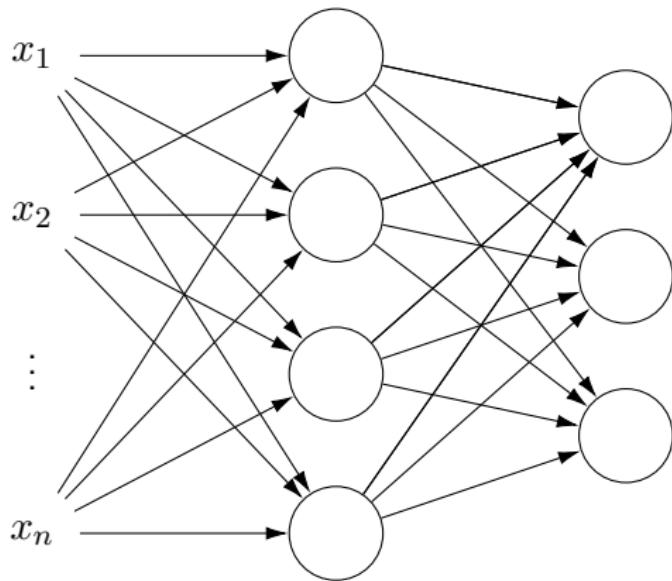
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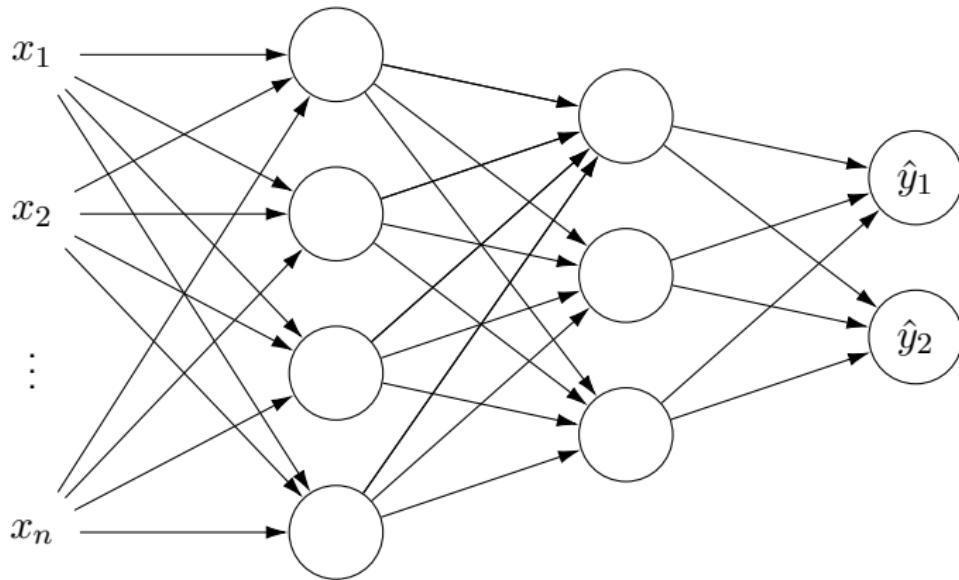
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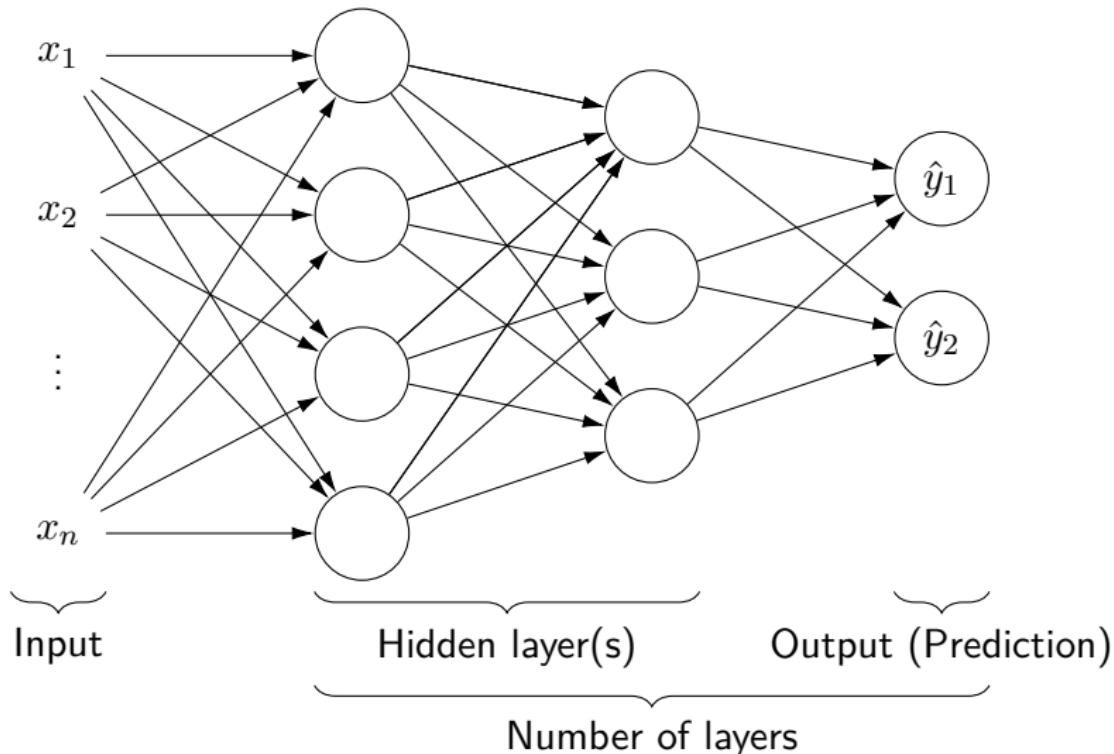
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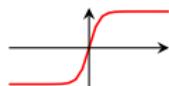
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- $\tanh(z)$



- The ReLU function:

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



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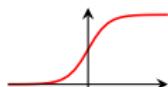


- The ReLU function:



- The logistic function (also called sigmoid function):

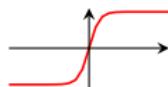
$$\sigma(z) = \frac{1}{1 + \exp(-z)}$$



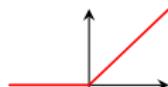
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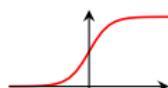
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- The softmax function:

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

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

## Loss Function

Measure of error between a prediction  $f(x)$  and a ground truth  $y$ .

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- Cross-entropy loss for classification with  $C$  classes ( $\mathcal{Y} = \{1, \dots, C\}$ )
  - $y \in \mathcal{Y}$
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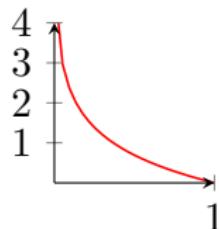
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# Regularization

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

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

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<sup>1</sup>MLE stands for Maximum Likelihood Estimation.

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## Training Objective

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$$\mathbb{E}_{(x,y) \in \mathcal{D}} \mathcal{L}(f(x; \theta), y)$$

## Training Objective

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$$J(\theta) = \mathbb{E}_{(x,y) \in \mathcal{D}} \mathcal{L}(f(x; \theta), y)$$

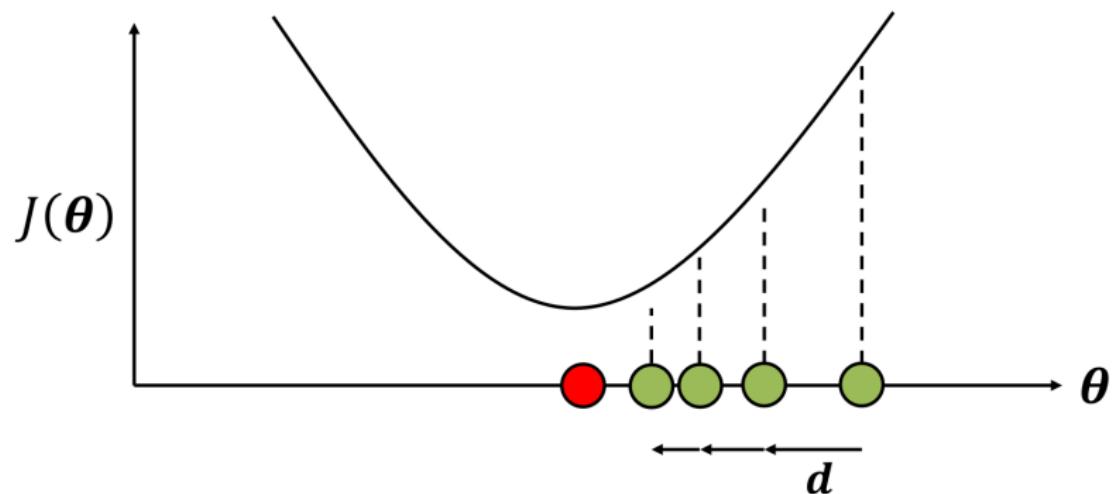
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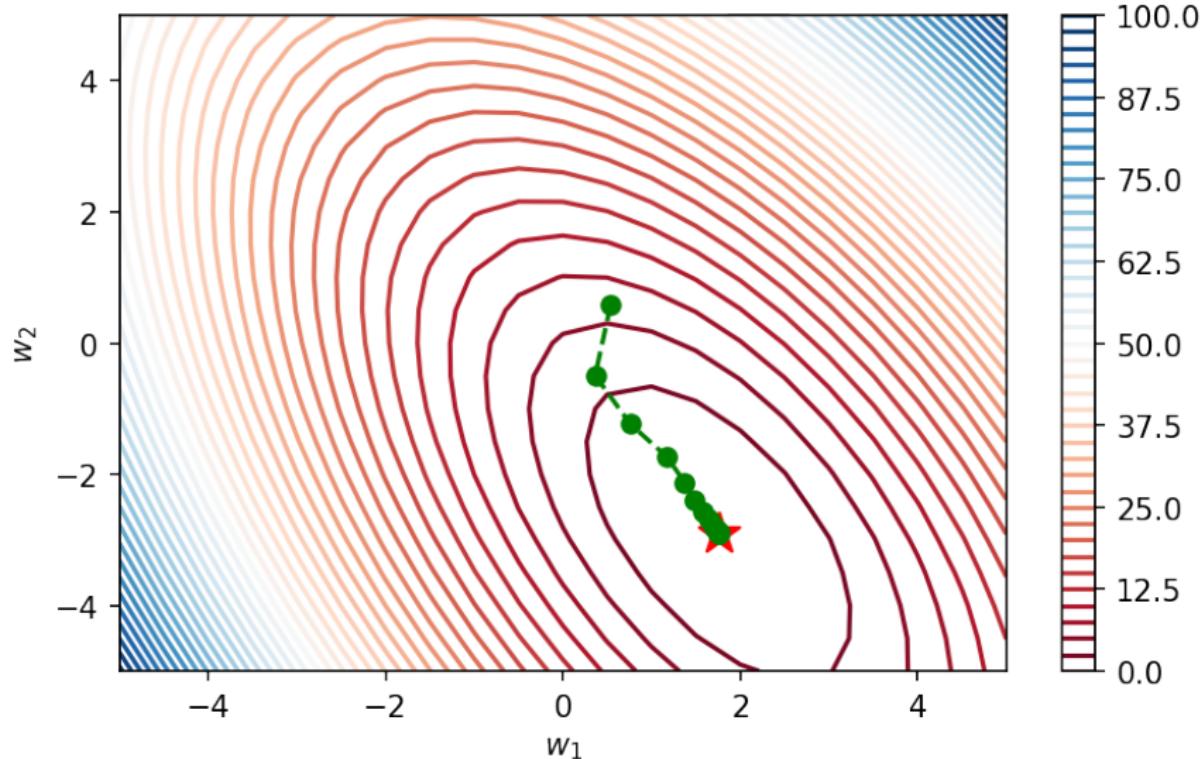
$$\begin{aligned} J(\theta) &= \mathbb{E}_{(x,y) \in \mathcal{D}} \mathcal{L}(f(x; \theta), y) \\ &\approx \frac{1}{N} \sum_{i=1}^N \mathcal{L}(f(x_i; \theta), y_i) \end{aligned}$$

# Gradient Descent



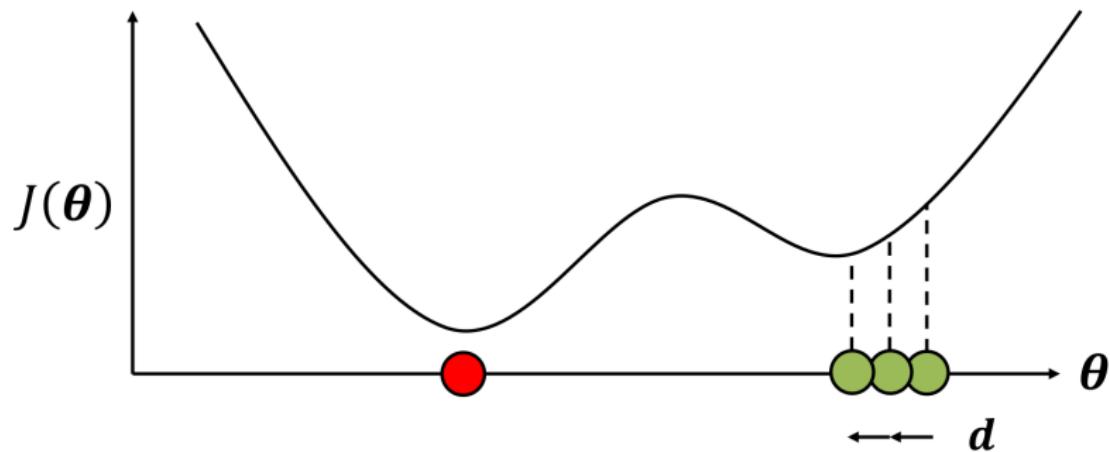
From Université Laval GLO-7030 by Ludovic Trottier

# Gradient Descent



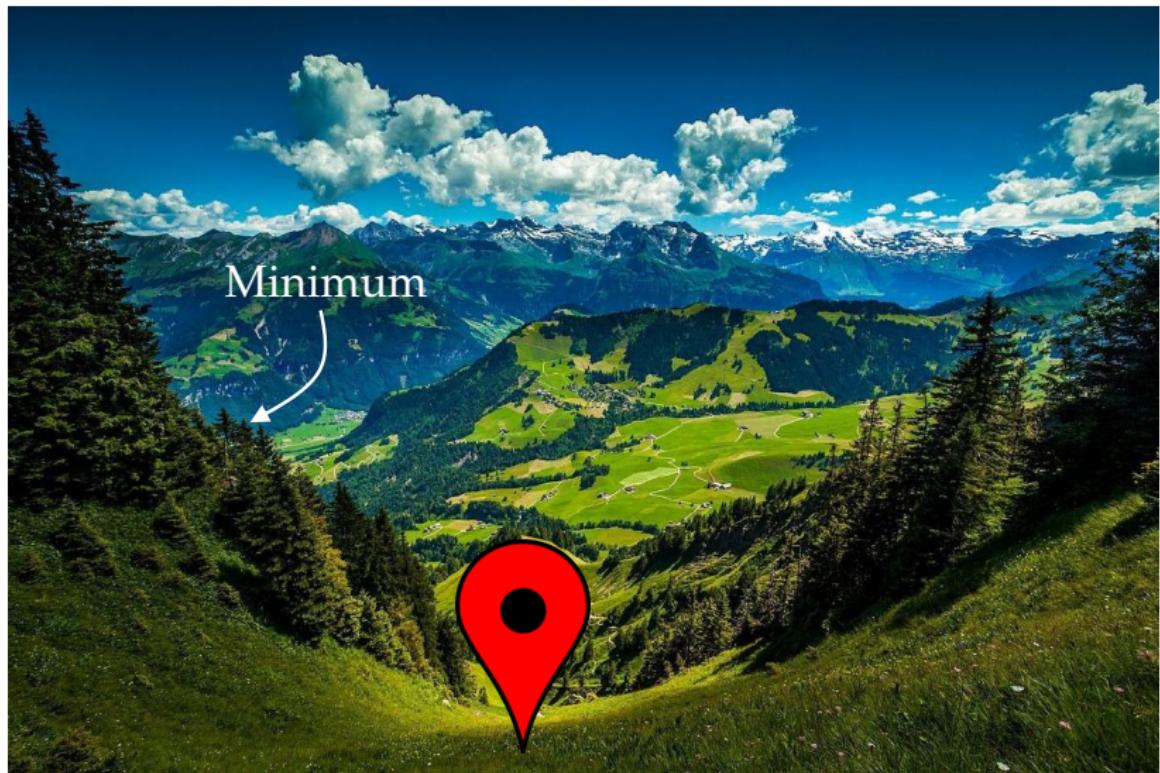
From Université Laval GLO-7030 by Pascal Germain

# 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

# Gradient Descent For Deep Neural Networks

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



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

## 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**.

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

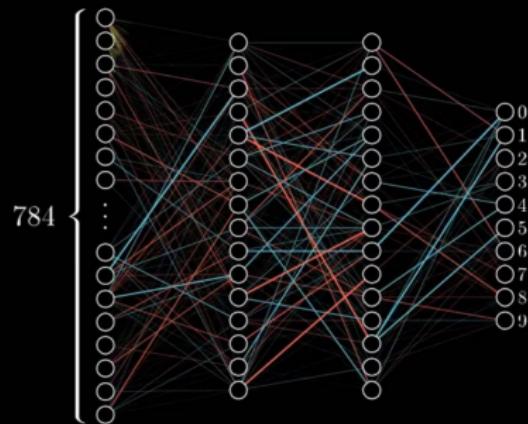
To update the parameters:

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

$\epsilon$  is called the learning rate.

# Gradient

Training in progress. . .



Extrait de <https://youtu.be/IHZwWFHwa-w> 3Blue1Brown

# Optimization Algorithms

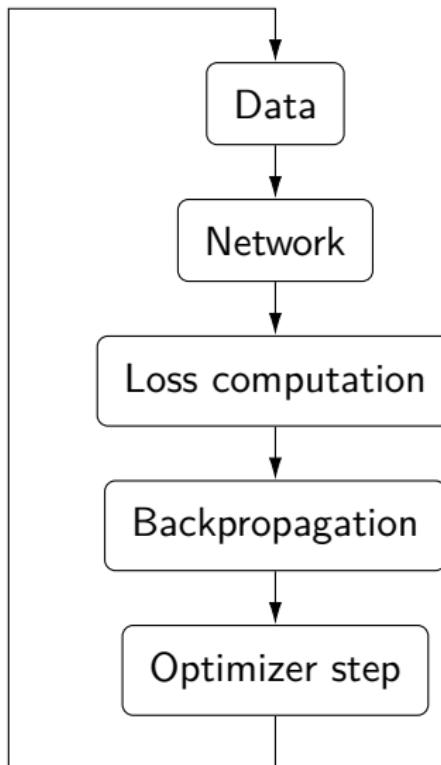
Simplest update rule:

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

Many types exist:

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

# Training Procedure



# Training Procedure

**procedure** TRAIN( $f(\cdot; \theta)$ ,  $S$ )

**input:** Neural network  $f$  parameterized by  $\theta$

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

**end procedure**

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        Let  $S' = S$

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

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$$d = \nabla_{\theta} \ell$$

            Update  $\theta$  with  $d$  using chosen optimizer  
(e.g.  $\theta \leftarrow \theta - \epsilon d$ ).

**end while**

**end for**

**end procedure**

## Deep Learning Libraries



TensorFlow

PyTorch

## Deep Learning Libraries



TensorFlow



# PyTorch Demo

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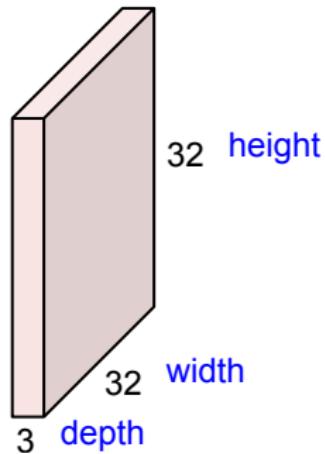
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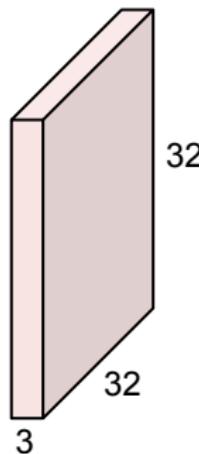
# Convolution Layer



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

# Convolution Layer

32x32x3 image

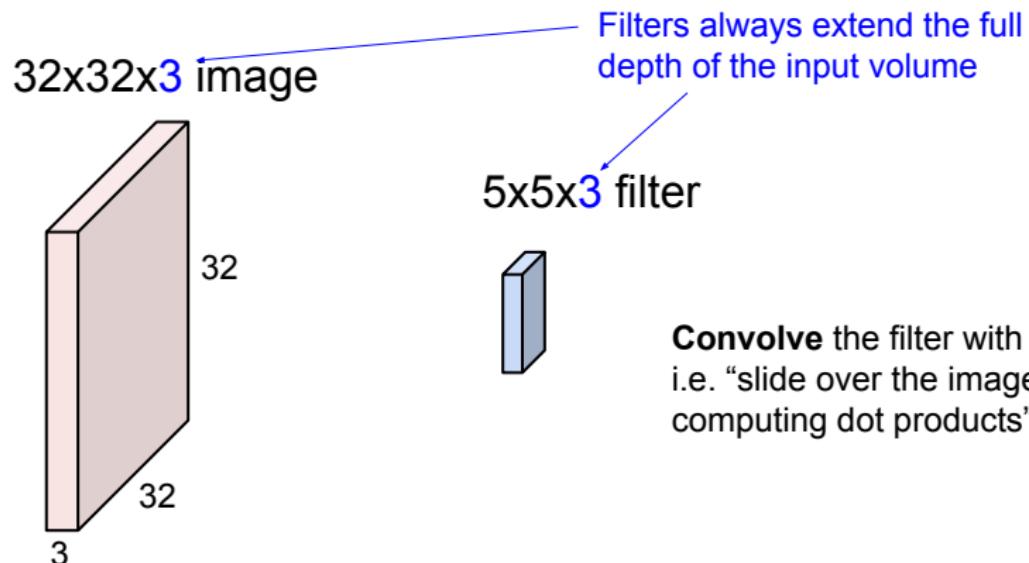


5x5x3 filter



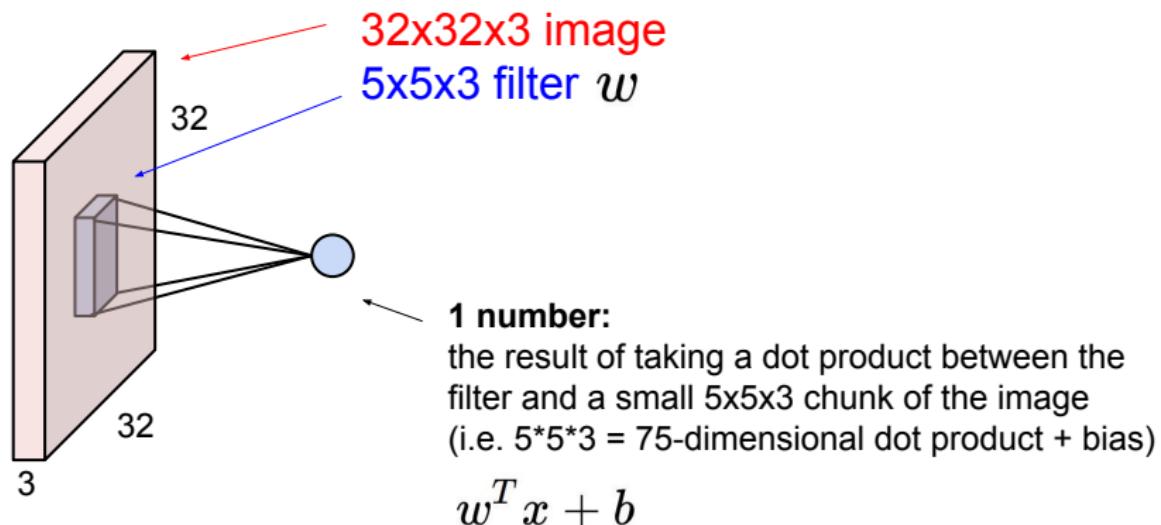
**Convolve** the filter with the image  
i.e. “slide over the image spatially,  
computing dot products”

# Convolution Layer



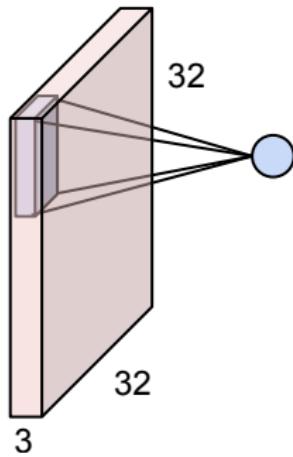
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

# Convolution Layer



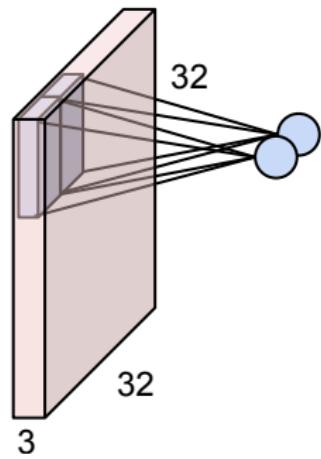
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

# Convolution Layer



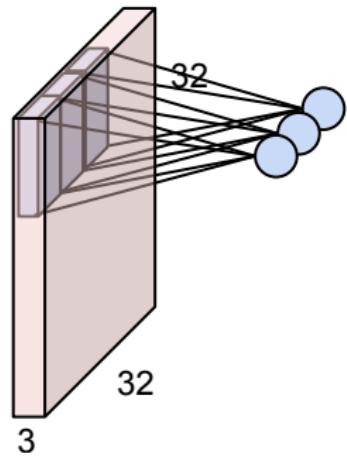
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

# Convolution Layer



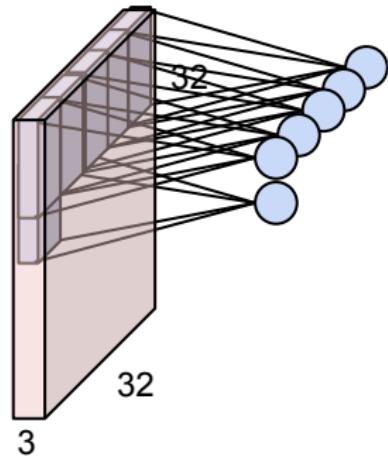
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

# Convolution Layer



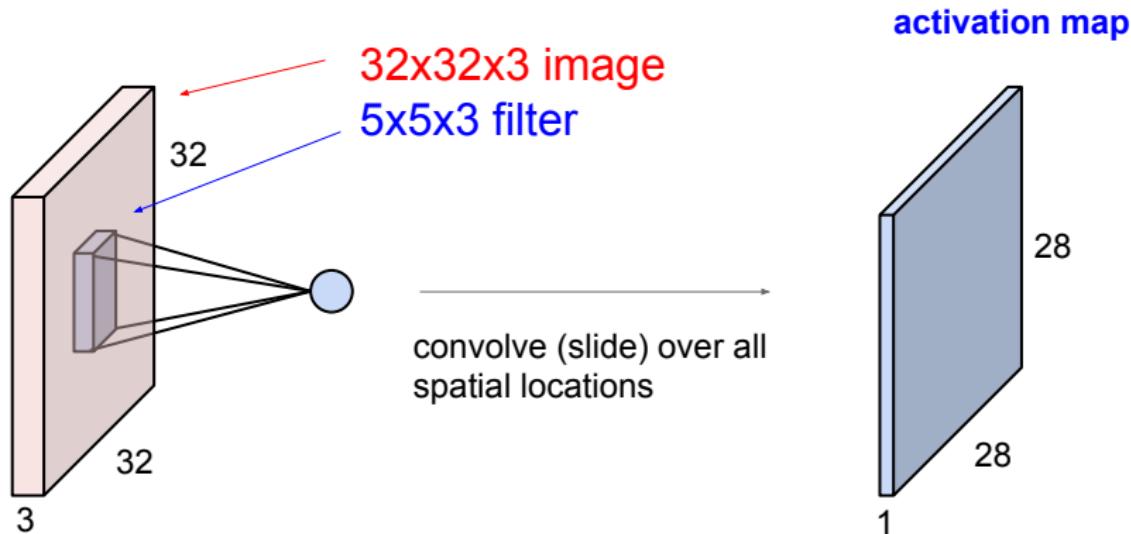
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

# Convolution Layer



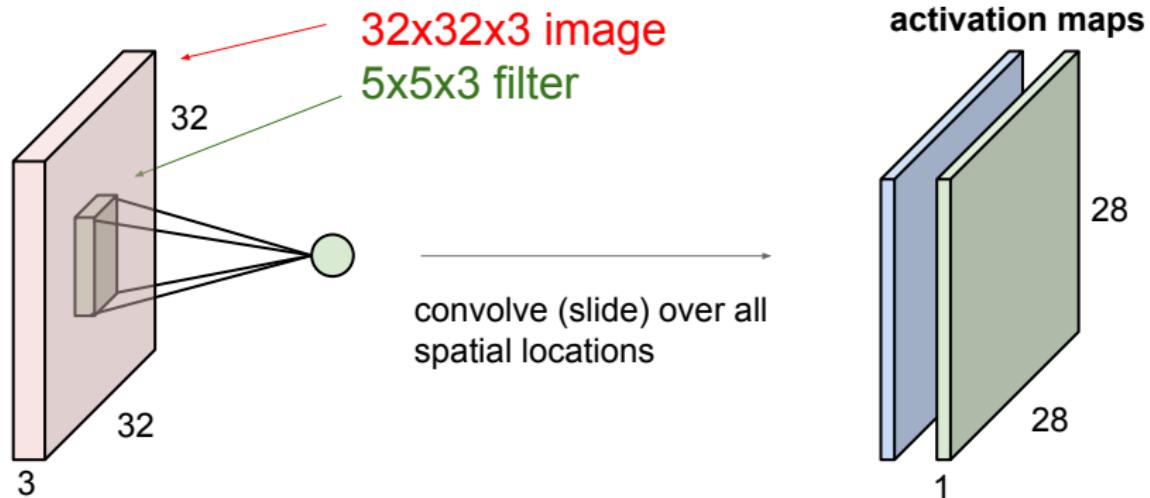
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

# Convolution Layer



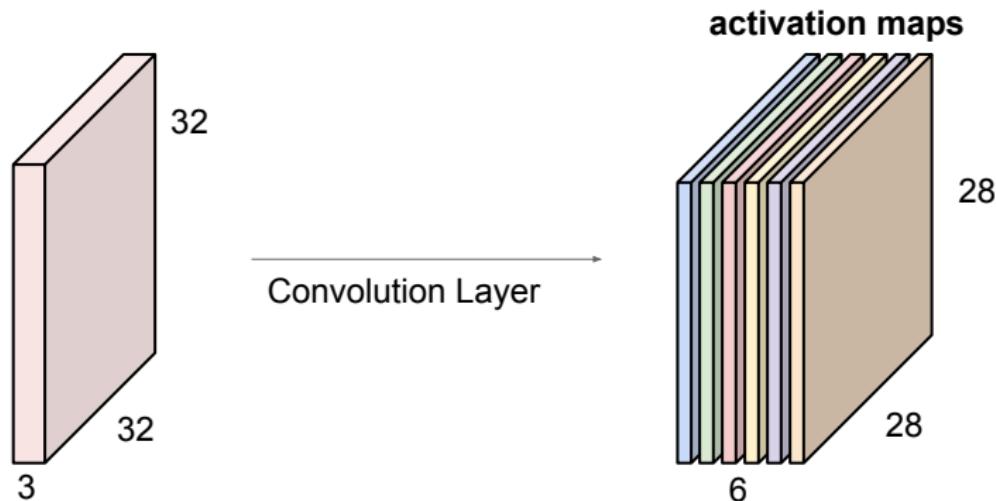
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

# Convolution Layer



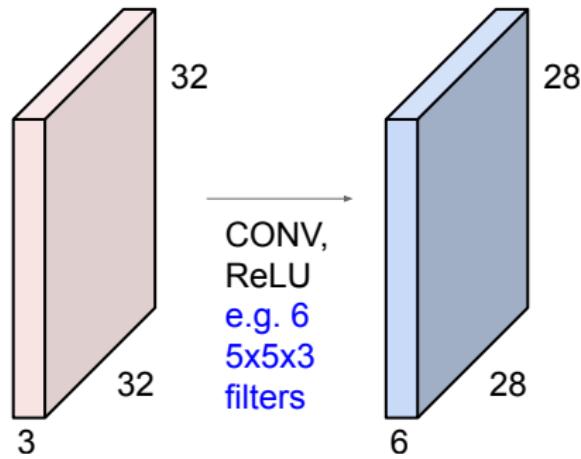
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

# Convolution Layer



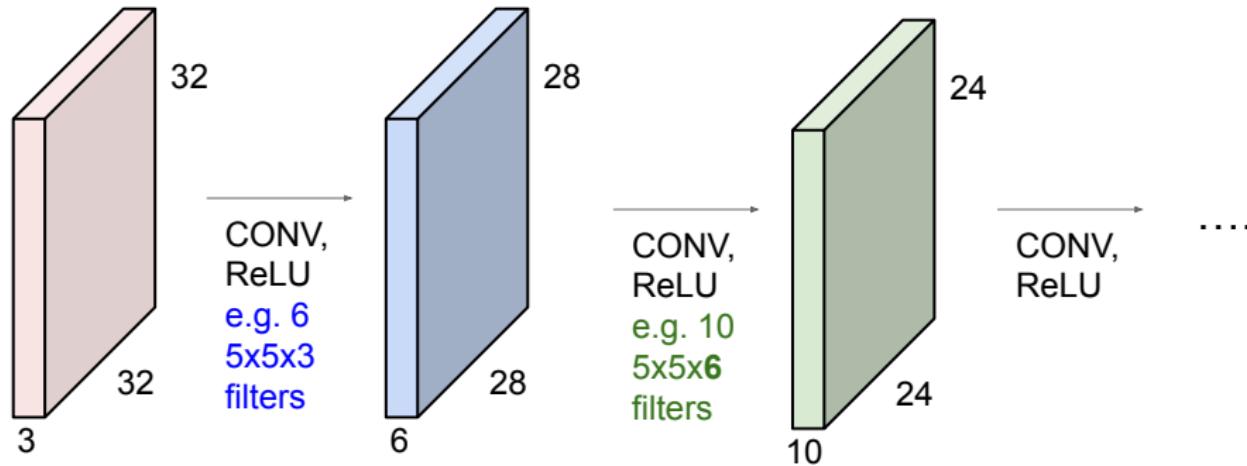
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

# Convolution Layer



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

# Convolution Layer



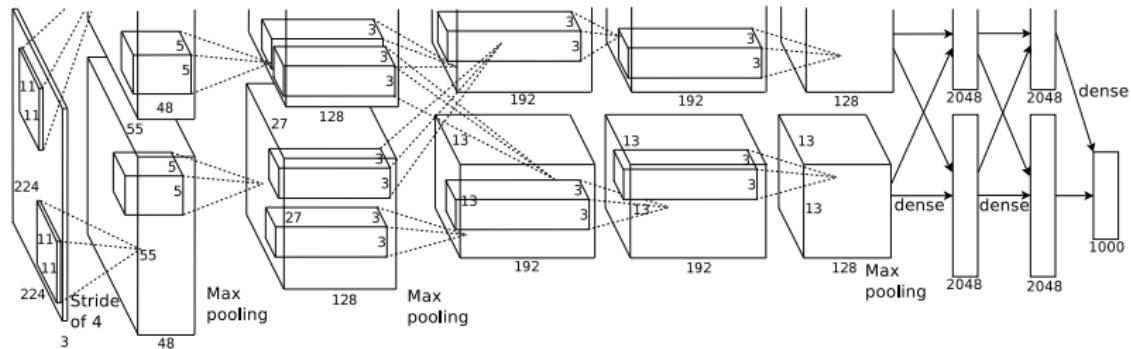
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

## Other Types of Layers

Many types of layers exist. Here is a few.

- Max pooling/average pooling
- Batch normalization
- Dropout

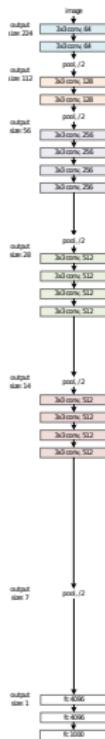
# Deep Neural Network Architectures



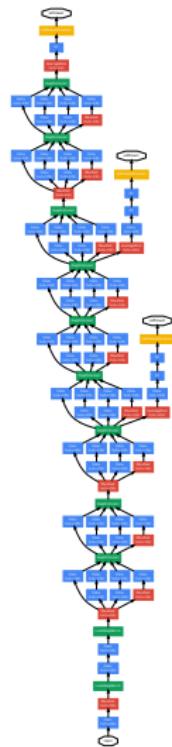
AlexNet

[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*.

## Bibliography II

-  Redmon, Joseph and Ali Farhadi (2017). "YOLO9000: better, faster, stronger". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7263–7271.
-  Simonyan, Karen and Andrew Zisserman (2014). "Very deep convolutional networks for large-scale image recognition". In: *arXiv preprint arXiv:1409.1556*.
-  Szegedy, Christian et al. (2015). "Going deeper with convolutions". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1–9.