

Introduction to Deep Learning

Bootcamp IID 2022

Frédérik Paradis

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2 mai 2022



UNIVERSITÉ
LAVAL

1 Who Am I?

2 Introduction

3 Neural Networks

4 Training

5 Convolutional Networks

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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?

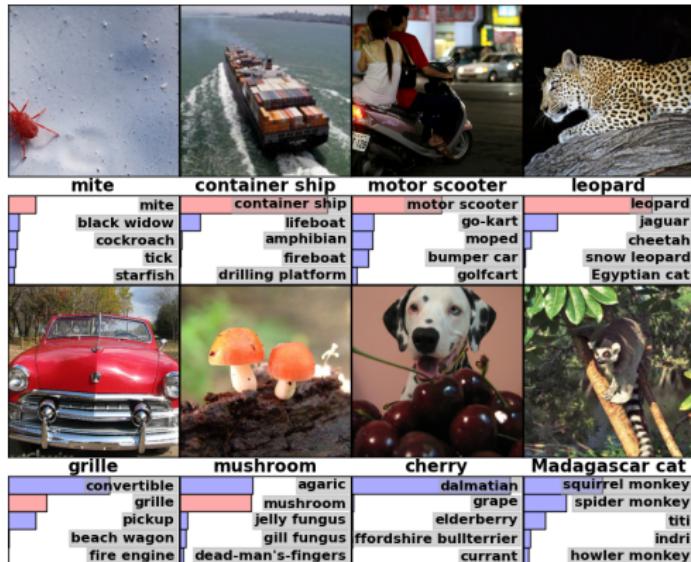
2 Introduction

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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

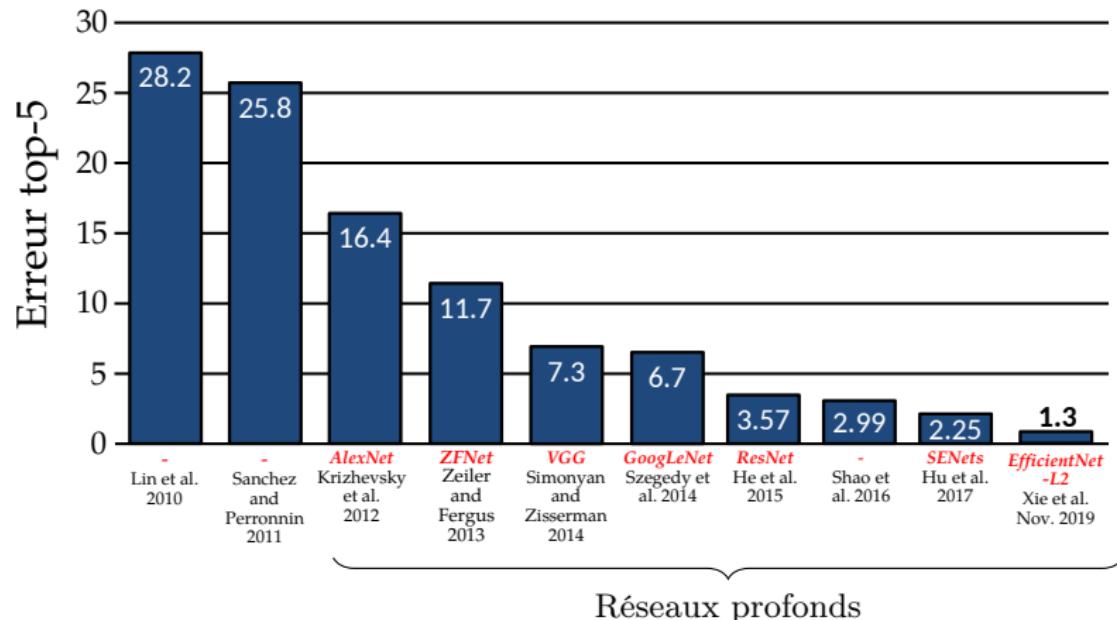
grille, convertible, agaric, dalmatian, squirrel monkey, grape, spider monkey, elderberry, titi, ffordshire bullterrier, currant, howler monkey, titi, indri

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

Computer Vision

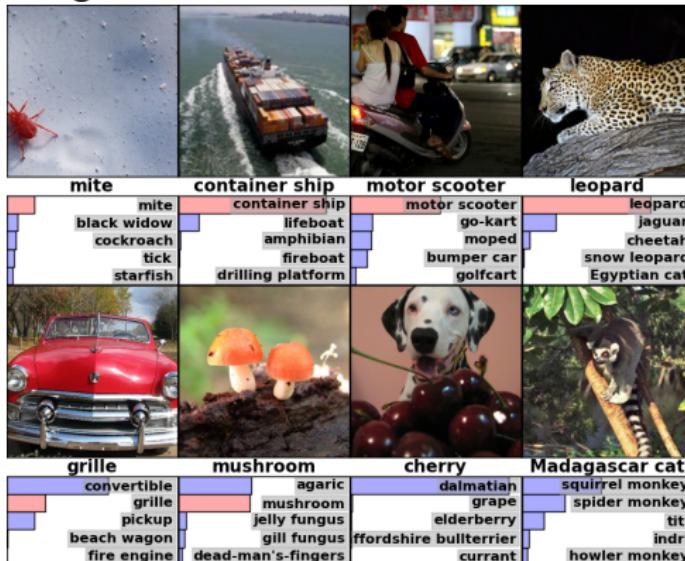
Large Scale Visual Recognition Challenge (LSVRC)

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



Computer Vision

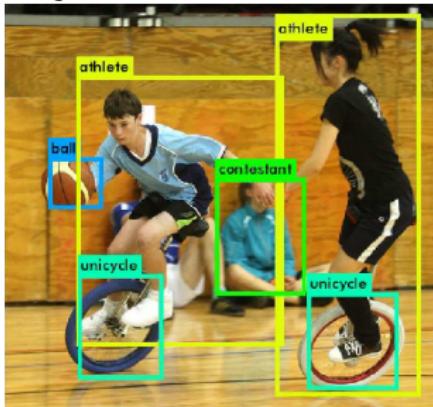
■ Image classification



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

Computer Vision

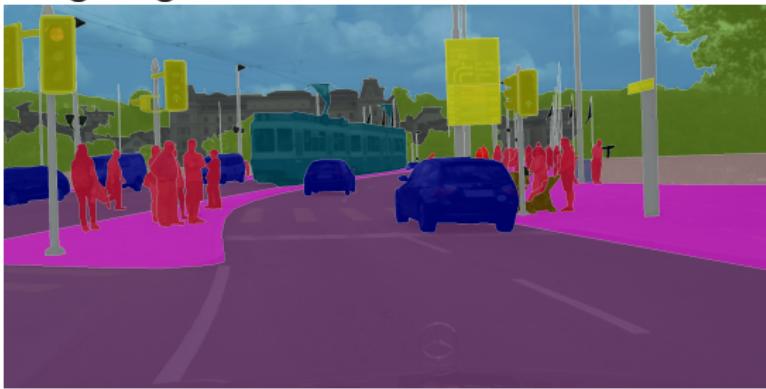
- Image classification
- Object detection



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

Computer Vision

- Image classification
- Object detection
- Image segmentation



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

Computer Vision

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

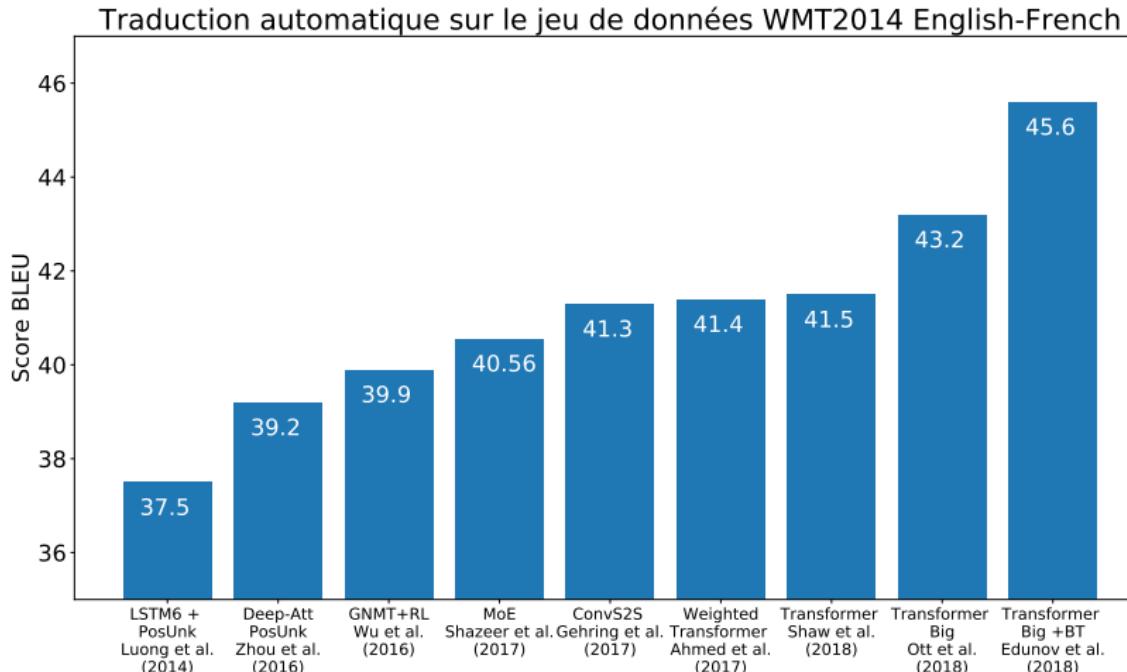


[Jesorsky et al. 2001, "Robust face detection using the hausdorff distance"]

Computer Vision

- Image classification
- Object detection
- Image segmentation
- Image matching (e.g. facial recognition)
- 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 other UI elements like language selection dropdowns and a character count indicator.

DÉTECTOR LA LANGUE ANGLAIS FRANÇAIS ARABE ▾ ▾
FRANÇAIS ANGLAIS ARABE ▾

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

25 / 5000

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Natural Language Processing

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



John Doe

★★★★★ **Awesome product**

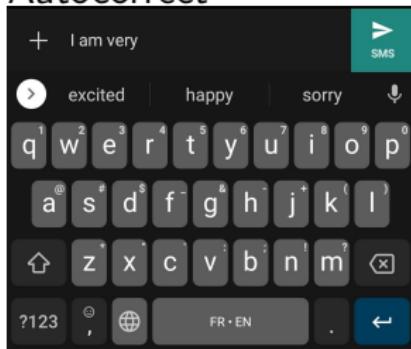
Reviewed in Canada on May 04, 2021

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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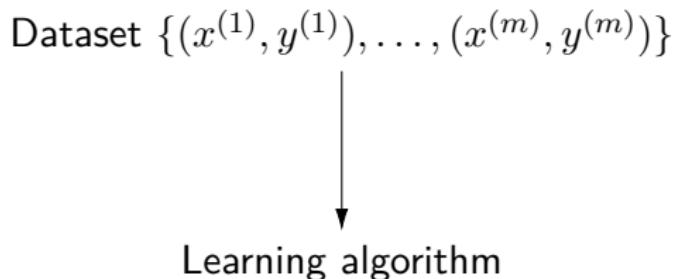
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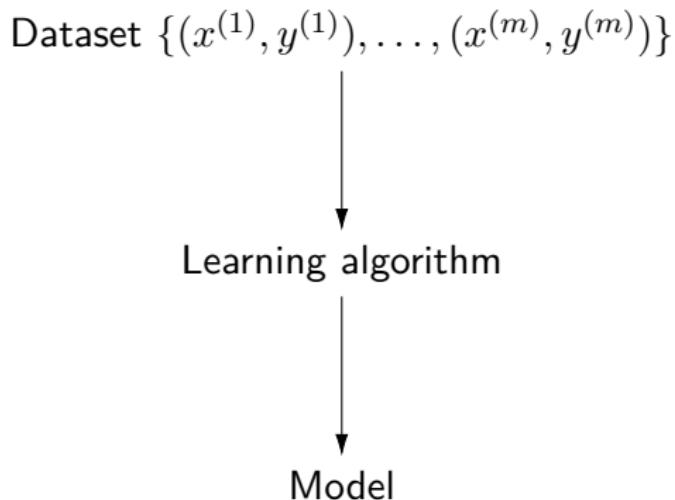
Machine Learning

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

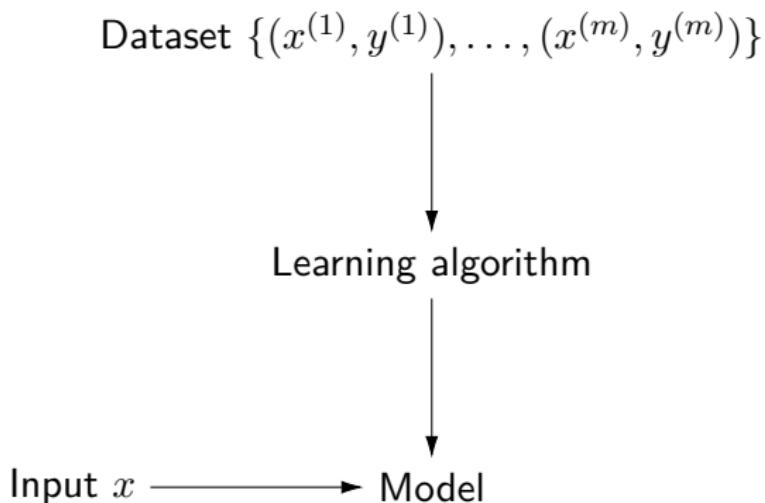
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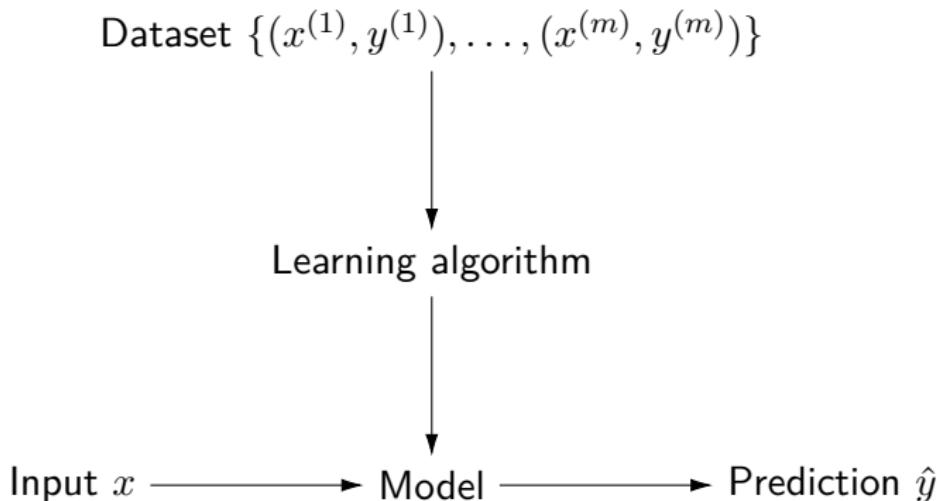
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Machine Learning



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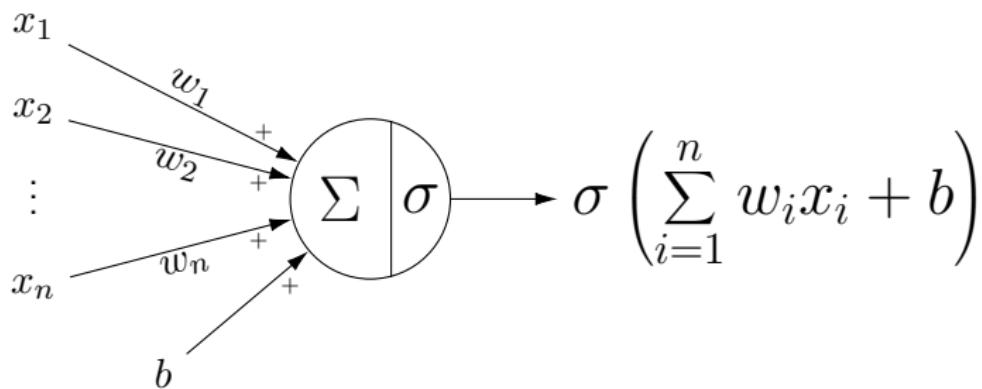


The Basis of Neural Networks: The Neuron

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

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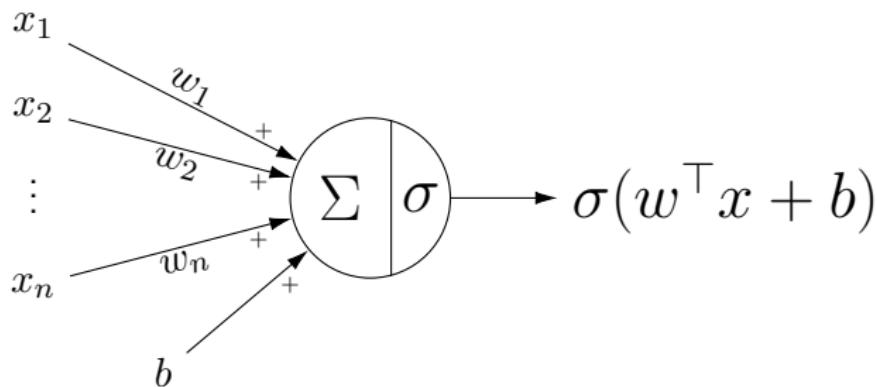
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where w are called the weights of the neuron and $\sigma(\cdot)$ is a non-linear activation function.

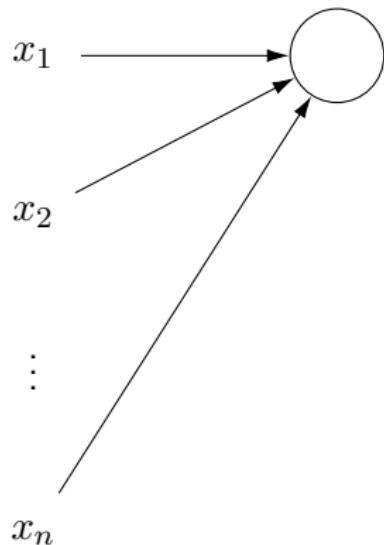
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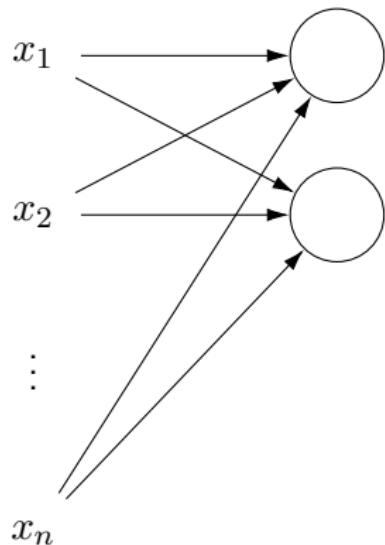


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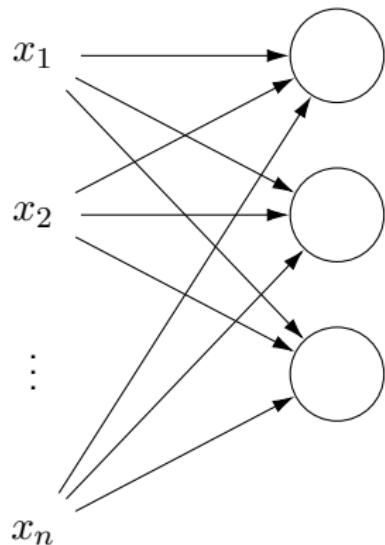
Neural Network



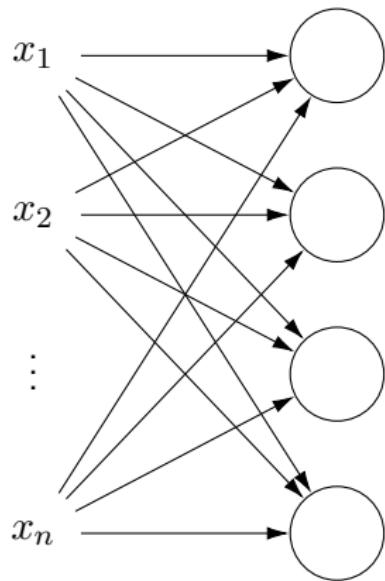
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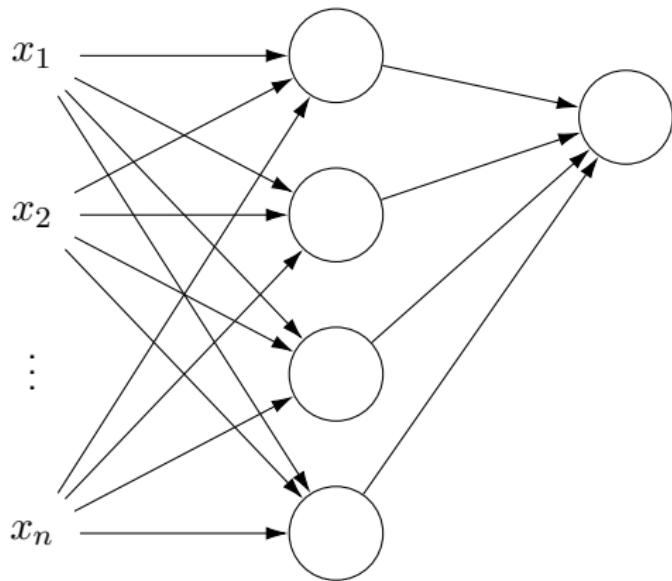
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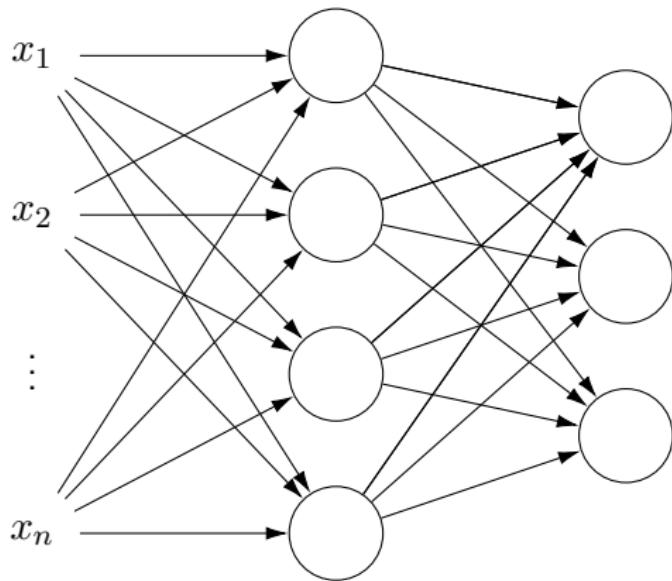
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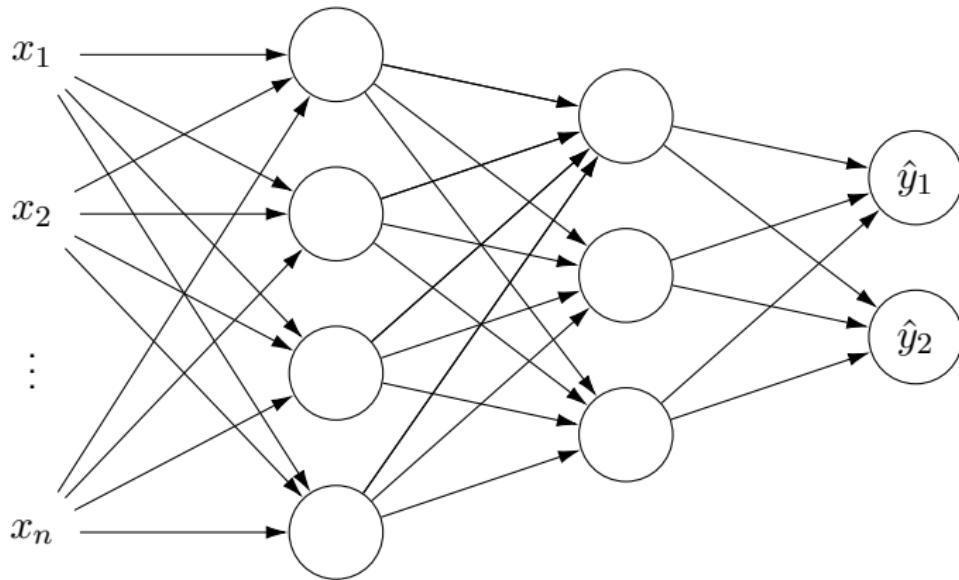
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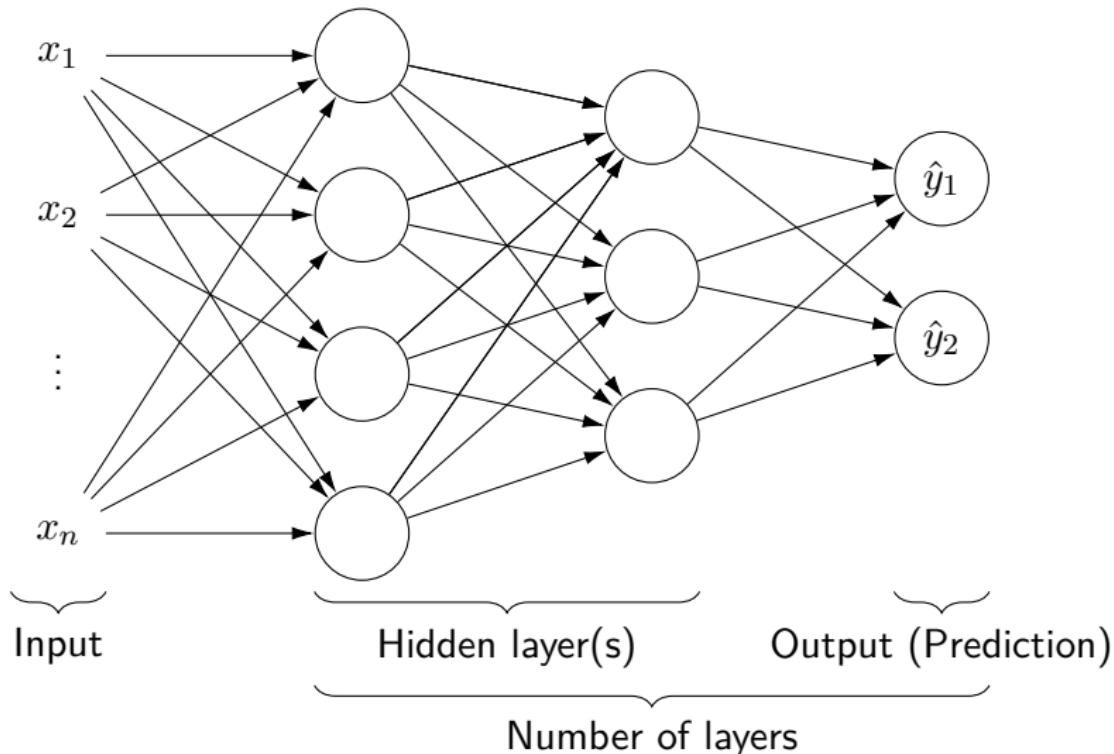
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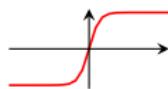
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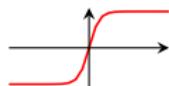
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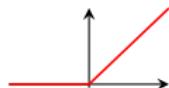
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- The ReLU function:

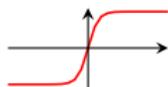
$$\text{ReLU}(z) = \max(0, z)$$



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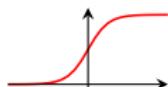


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- The logistic function (also called sigmoid function):

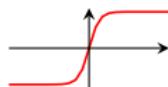
$$\sigma(z) = \frac{1}{1 + \exp(-z)}$$



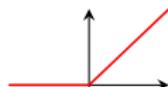
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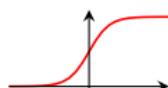
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- The softmax function:

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

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 ($\mathcal{Y} = \{1, \dots, C\}$)
 - $y \in \mathcal{Y}$
 - $f(x) = [f(x)_1, \dots, f(x)_C] = \text{softmax}([z_1, \dots, z_C])$

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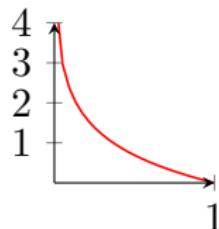
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Regularization

To avoid overfitting (i.e. learning the training examples by heart), we may add a penalty term to the loss¹:

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

¹MLE stands for Maximum Likelihood Estimation.

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Training Objective

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

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$$\mathcal{L}(f(x; \theta), y)$$

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

Training Objective

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

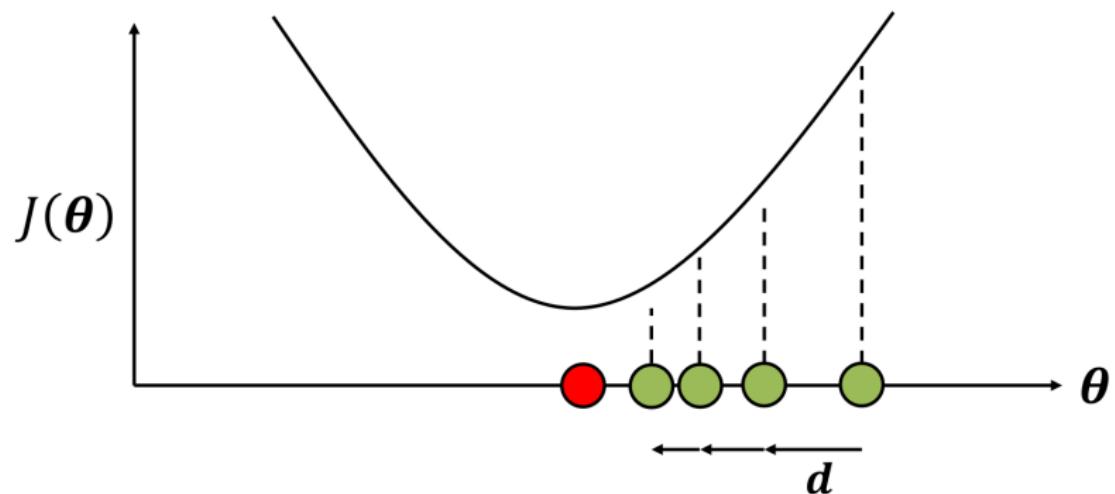
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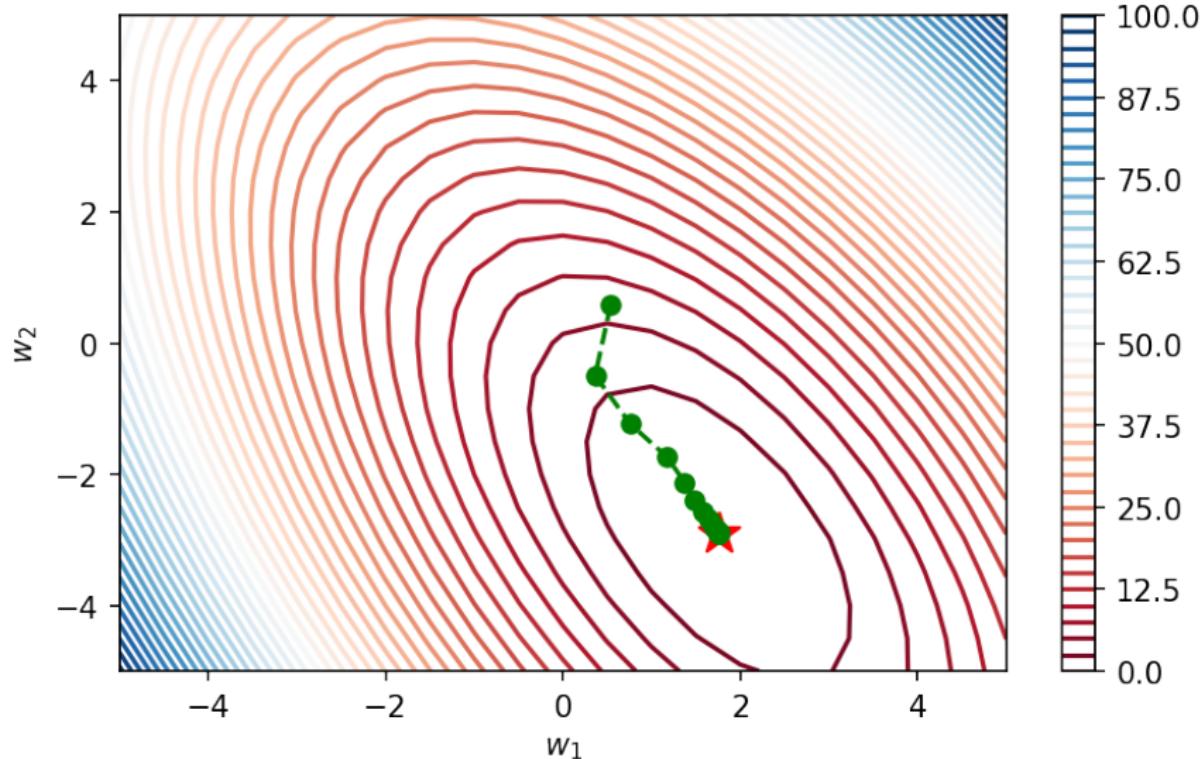
$$\begin{aligned} J(\theta) &= \mathbb{E}_{(x,y) \in \mathcal{D}} \mathcal{L}(f(x; \theta), y) \\ &\approx \frac{1}{N} \sum_{i=1}^N \mathcal{L}(f(x_i; \theta), y_i) \end{aligned}$$

Gradient Descent



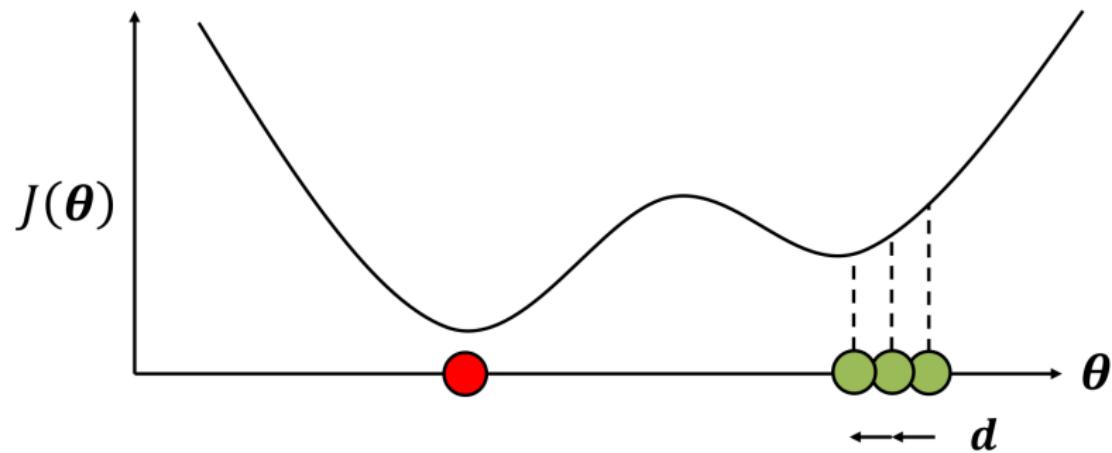
From Université Laval GLO-7030 by Ludovic Trottier

Gradient Descent



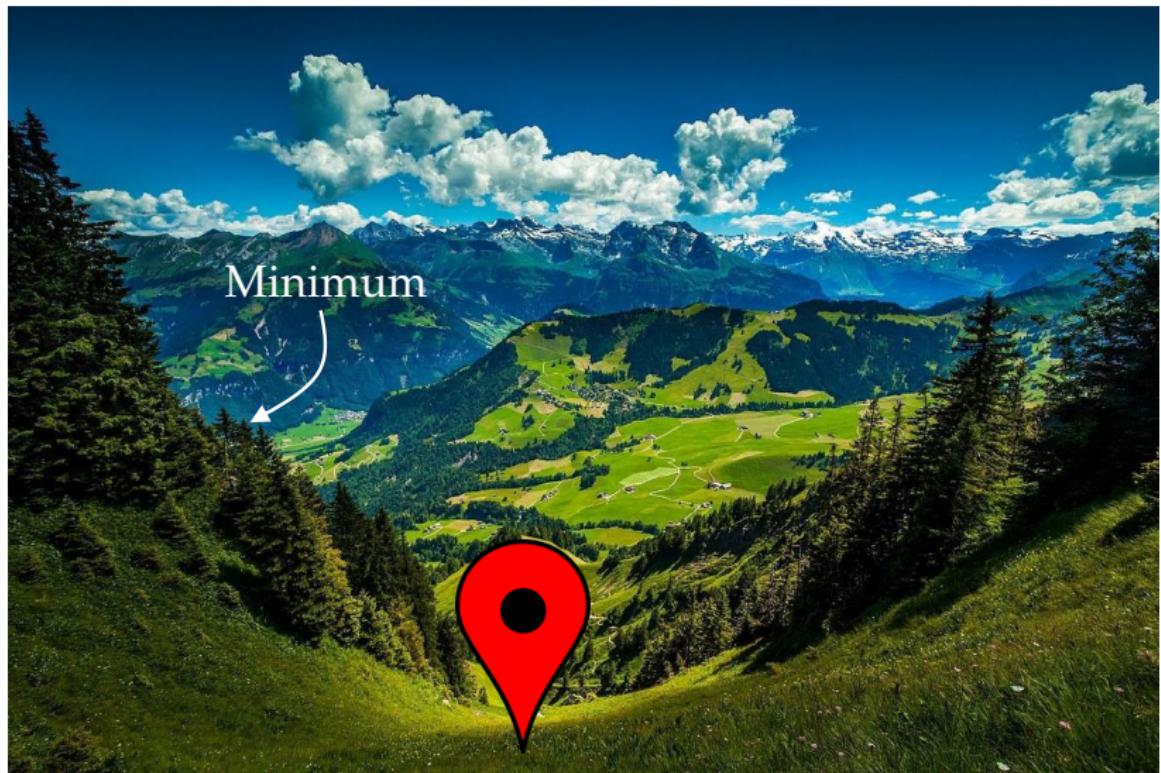
From Université Laval GLO-7030 by Pascal Germain

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**.

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

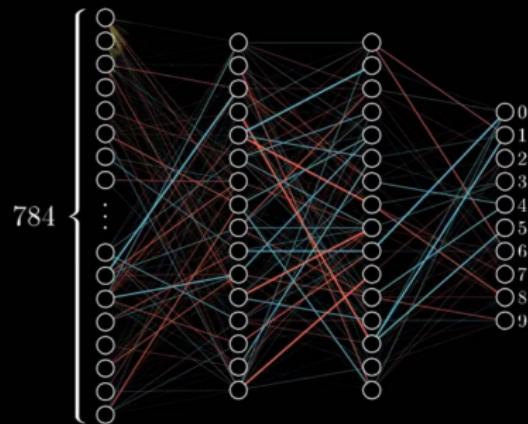
To update the parameters:

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

ϵ is called the learning rate.

Gradient

Training in progress. . .



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

Optimization Algorithms

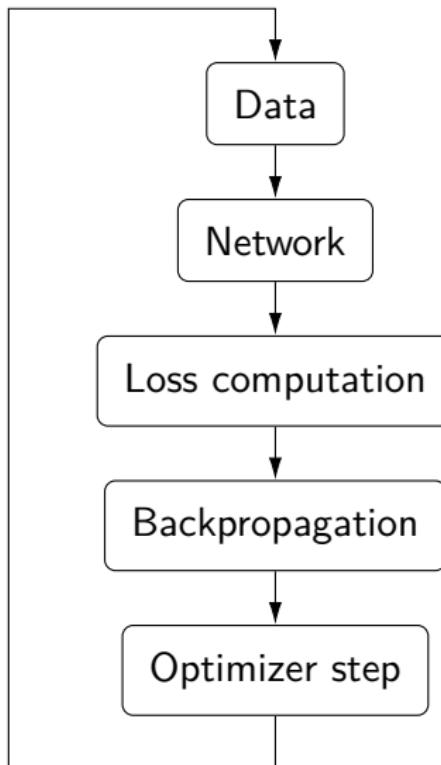
Simplest update rule:

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

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 θ

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

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' .

end while

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$$\ell = \frac{1}{b} \sum_{(x,y) \in B} \mathcal{L}(f(x; \theta), y)$$
$$d = \nabla_{\theta} \ell$$

 Update θ 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

1 Who Am I?

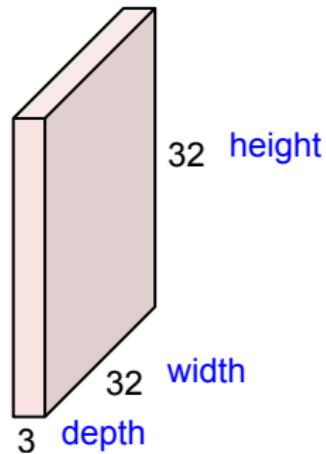
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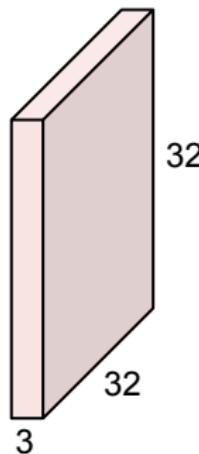
Convolution Layer



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

Convolution Layer

32x32x3 image

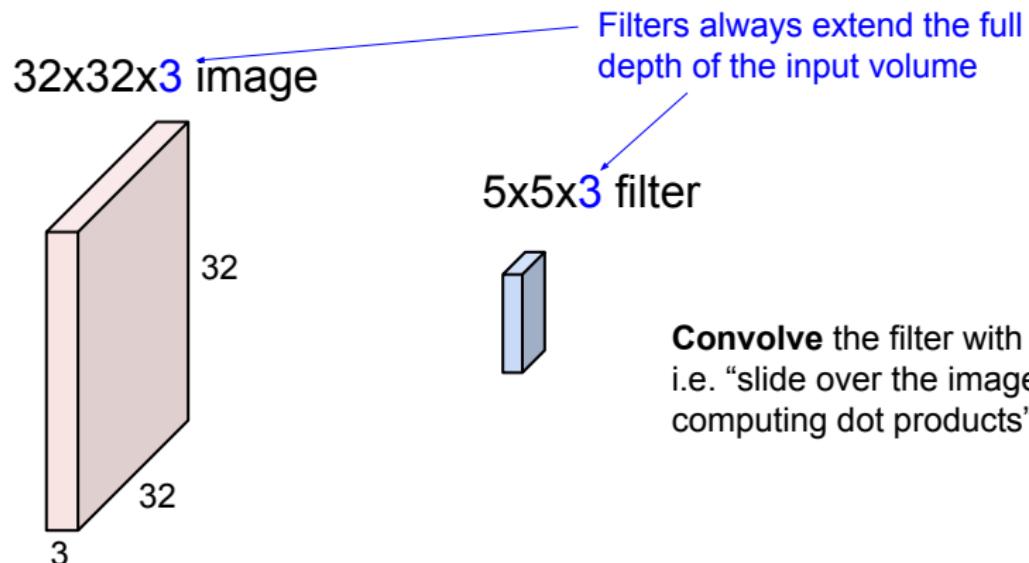


5x5x3 filter



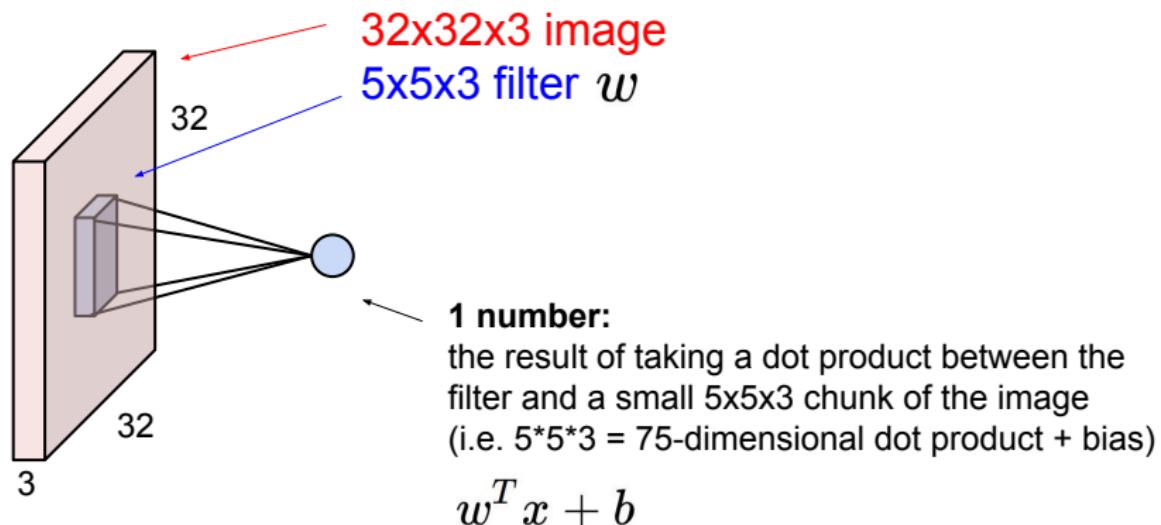
Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Convolution Layer



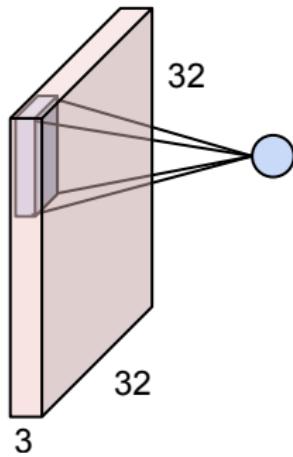
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



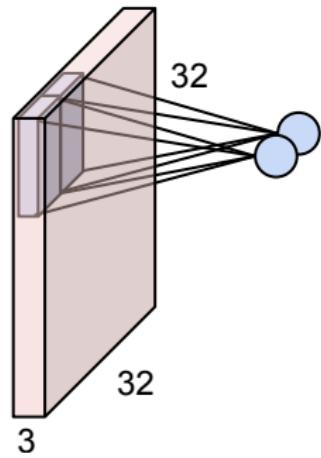
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



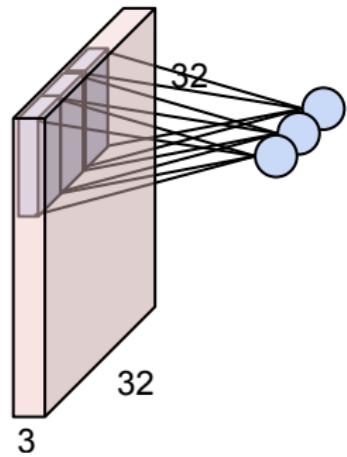
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Convolution Layer



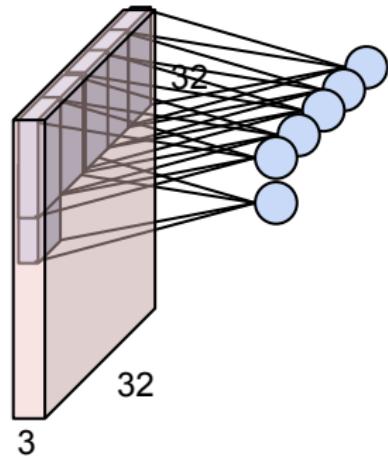
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Convolution Layer



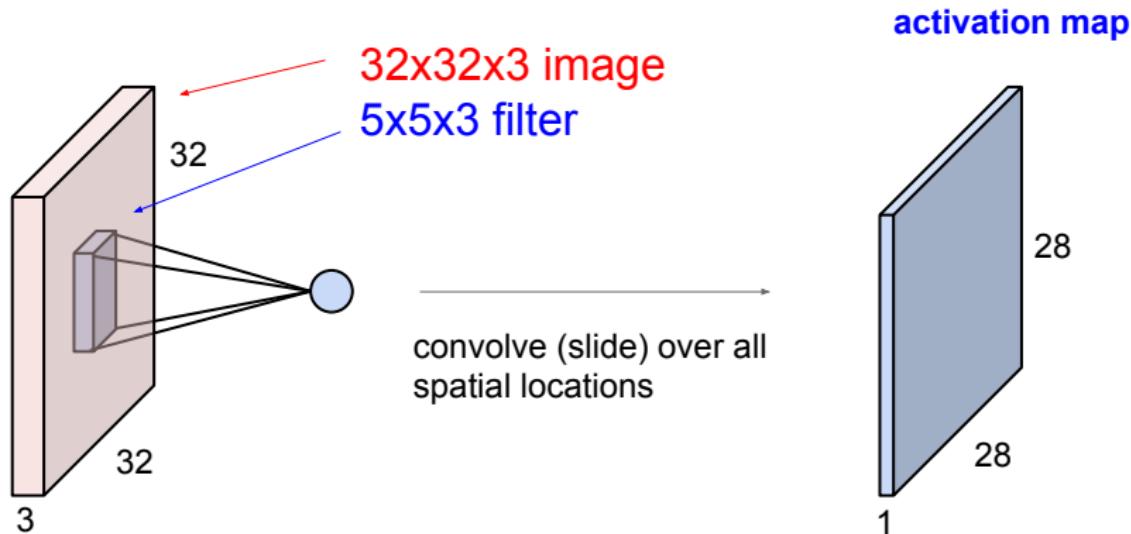
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Convolution Layer



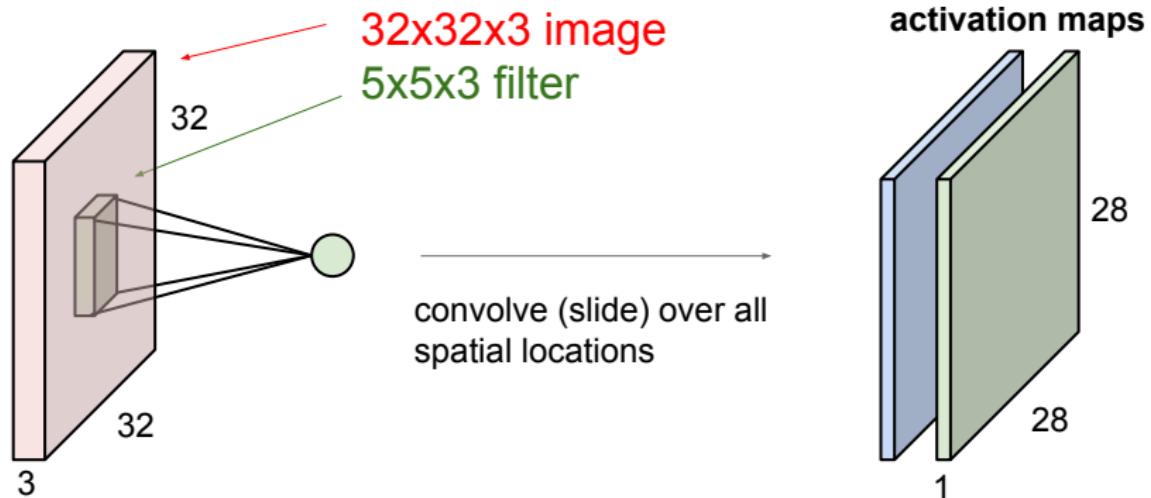
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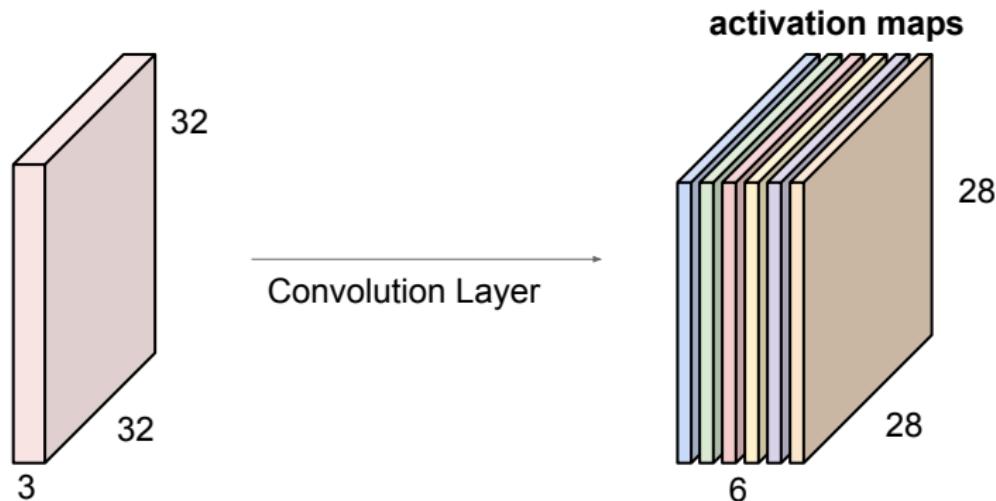
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Convolution Layer



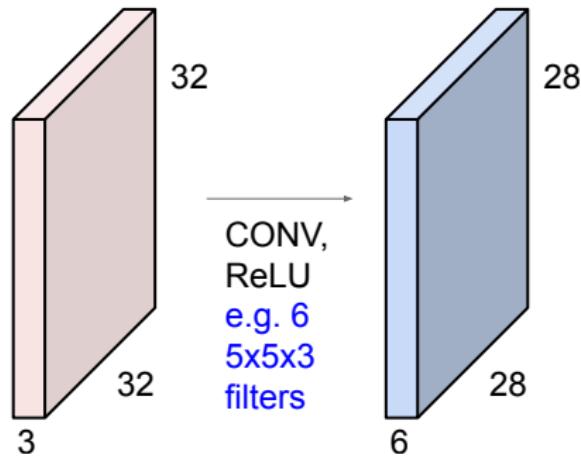
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Convolution Layer



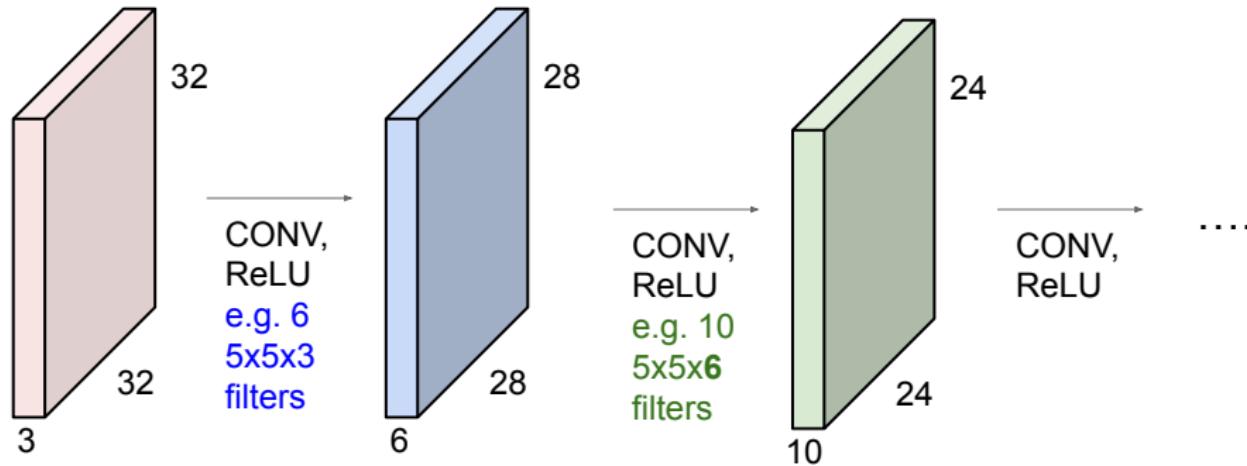
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



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Convolution Layer



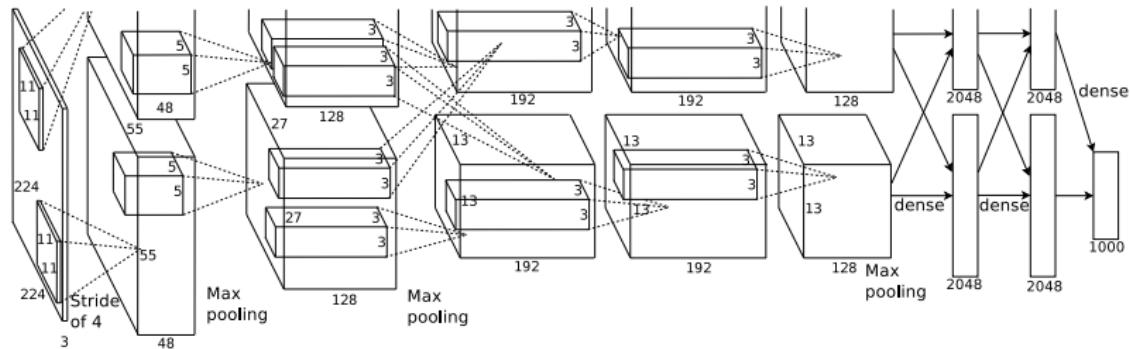
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Other Types of Layers

Many types of layers exist. Here is a few.

- Max pooling/average pooling
- Batch normalization
- Dropout

Deep Neural Network Architectures



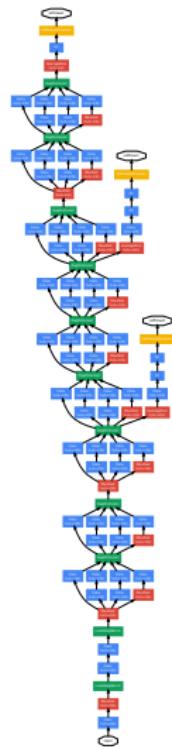
AlexNet

[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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-  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.
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-  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.

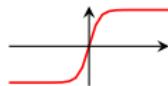
Activation Functions

Given a non-activated output $z = w^\top x + b$, then $\sigma(z) = \dots$

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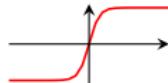
- $\tanh(z)$



Activation Functions

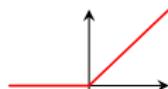
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- $\tanh(z)$



- The ReLU function:

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



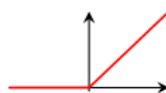
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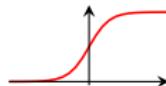


- The ReLU function:



- The logistic function (also called sigmoid function):

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



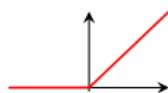
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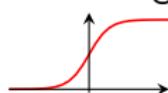
- $\tanh(z)$



- The ReLU function:



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- The softmax function:

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

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

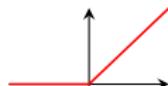
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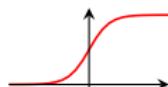
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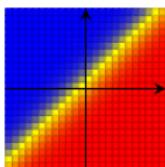
- The ReLU function:



- The logistic function (also called sigmoid function):



- The softmax function:



$$\text{softmax}(z)_1 = \frac{\exp(x)}{\exp(x)+\exp(y)} \text{ for } z = [x, y]$$

Loss Function

Measure of error between a prediction $\hat{y} = f(x)$ and a ground truth y .

Goal: minimize the loss function!

- Squared error (SE) for regression:

$$\mathcal{L}_{\text{SE}}(\hat{y}, y) = (\hat{y} - y)^2$$

for $\hat{y}, y \in \mathbb{R}$.

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$$H(q, p) = - \sum_{c \in \mathcal{Y}} p(c) \log q(c)$$

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where $p(c) = \mathbb{1}(y = c)$ and $q(c) = \hat{y}_c$. This simplifies to:

$$\mathcal{L}_{\text{CE}}(\hat{y}, y) = - \sum_{c=1}^C \mathbb{1}(y = c) \log \hat{y}_c = -\log \hat{y}_y$$