

Introduction to Deep Learning

Bootcamp IID 2024

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06 mai 2024

1 Introduction

2 Neural Networks

3 Training

4 Overfitting

Who Am I?



Jonas Ngnawé

🎓 Ph.D. Student at Université Laval
(IID & Mila)

[in jonas-ngnawe-bb7712a2](#)

Slides Credit: Frédéric Paradis, Mathieu Godbout et Alexandre Bouras

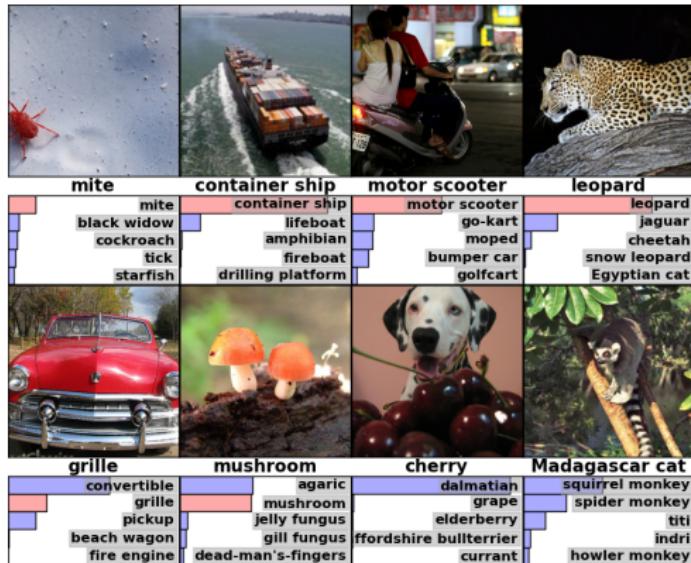
1 Introduction

2 Neural Networks

3 Training

4 Overfitting

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

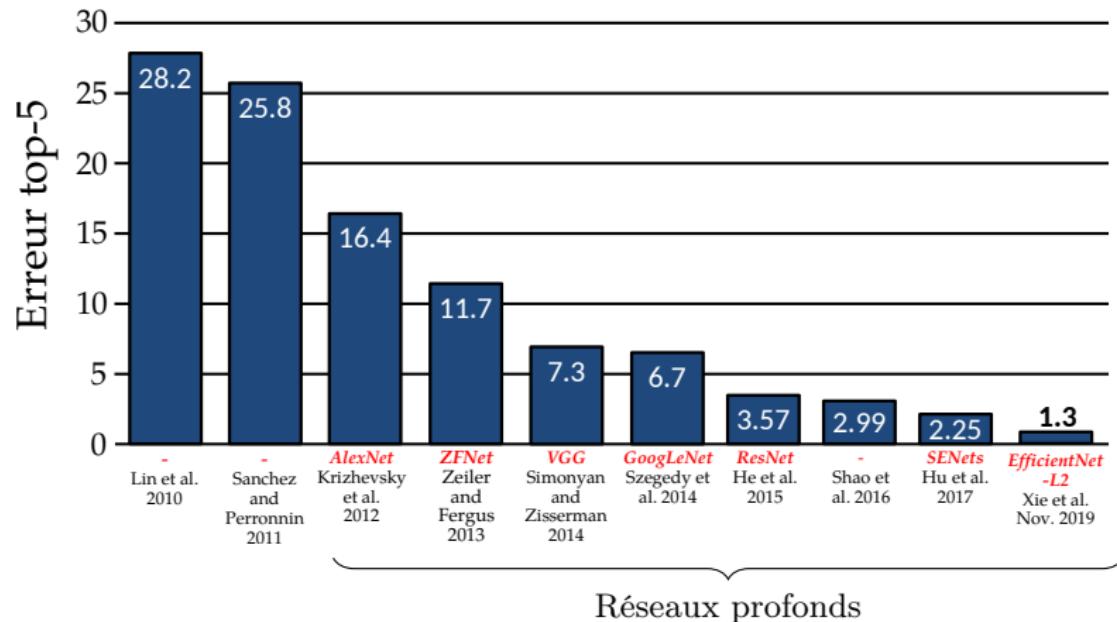
grille, convertible, agaric, dalmatian, squirrel monkey, grape, spider monkey, elderberry, titi, ffordshire bullterrier, currant, howler monkey, indri

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

Computer Vision

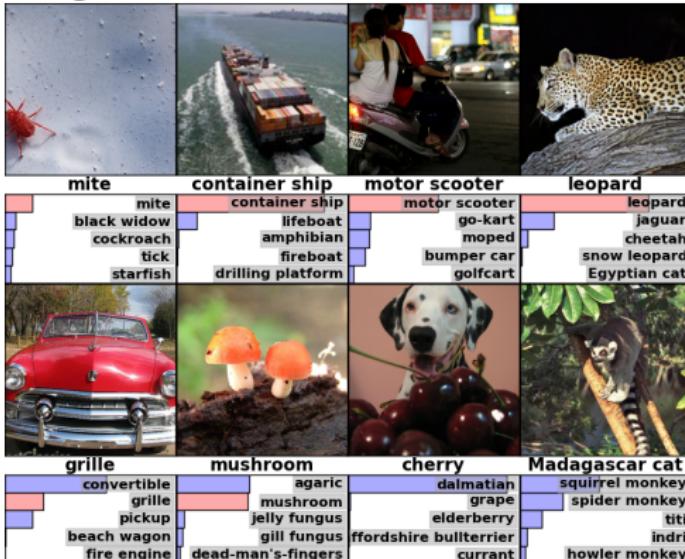
Large Scale Visual Recognition Challenge (LSVRC)

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



Computer Vision

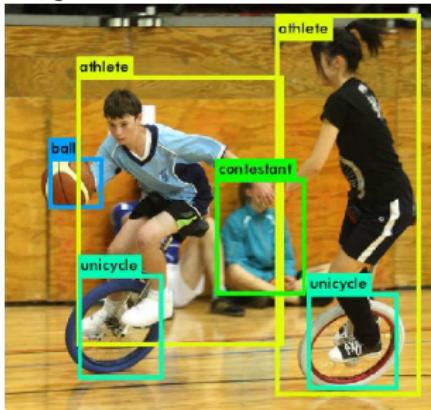
■ Image classification



[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

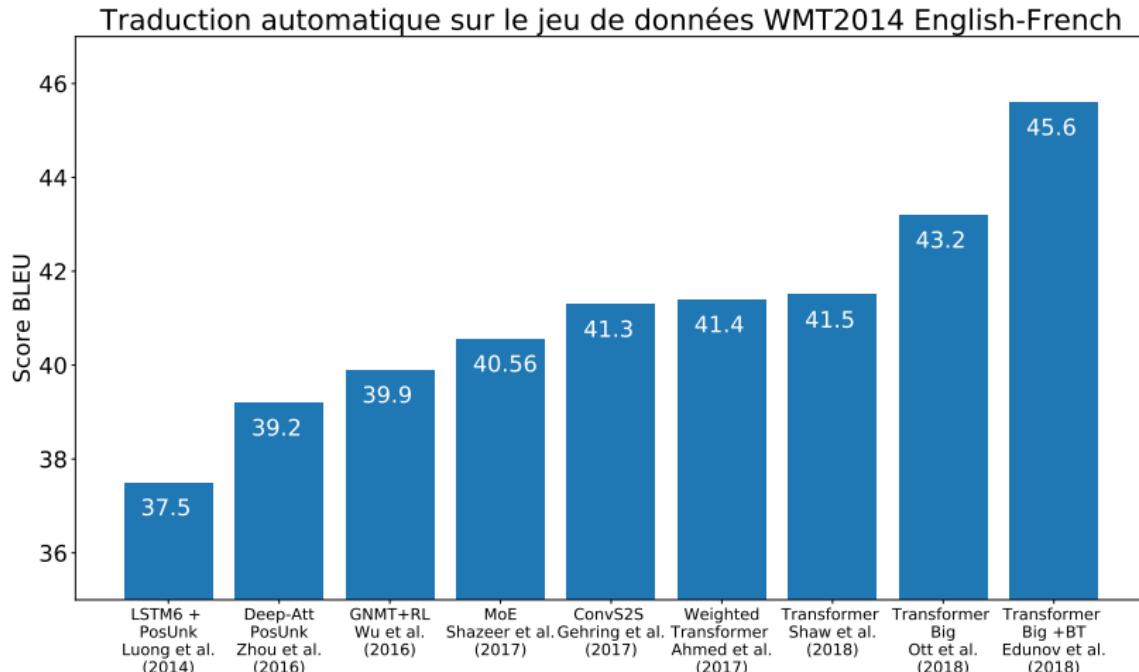
- Image classification
- Object detection
- Image segmentation
- Image generation



Computer Vision

- Image classification
- Object detection
- Image segmentation
- Image generation
- 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, and the right section is for output. Both sections have language selection menus at the top.

Input Section:

- Label: DÉTECTOR LA LANGUE
- Selected Language: ANGLAIS
- Text Input: Deep learning is awesome!
- Close button: X
- Bottom controls: A microphone icon, a speaker icon, and a progress bar indicating 25 / 5000.

Output Section:

- Label: FRANÇAIS
- Selected Language: FRANÇAIS
- Text Output: L'apprentissage en profondeur est génial! ☆
- Bottom controls: A microphone icon, a speaker icon, and a set of icons for copy, edit, and share.

Natural Language Processing

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



John Doe

★★★★★ **Awesome product**

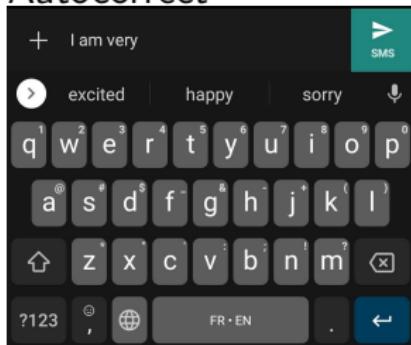
Reviewed in Canada on May 04, 2021

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

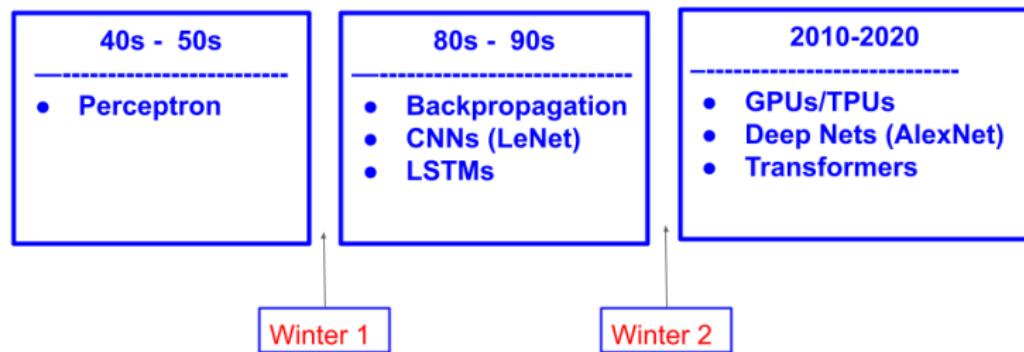
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Natural Language Processing

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

History Overview



1 Introduction

2 Neural Networks

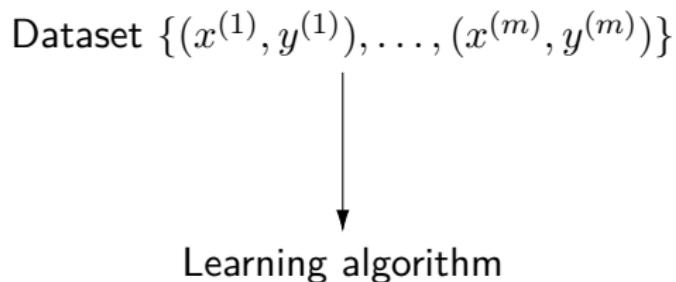
3 Training

4 Overfitting

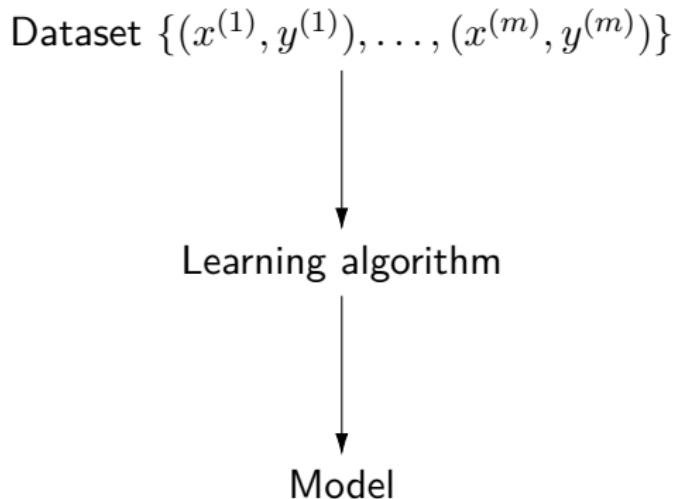
Machine Learning

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

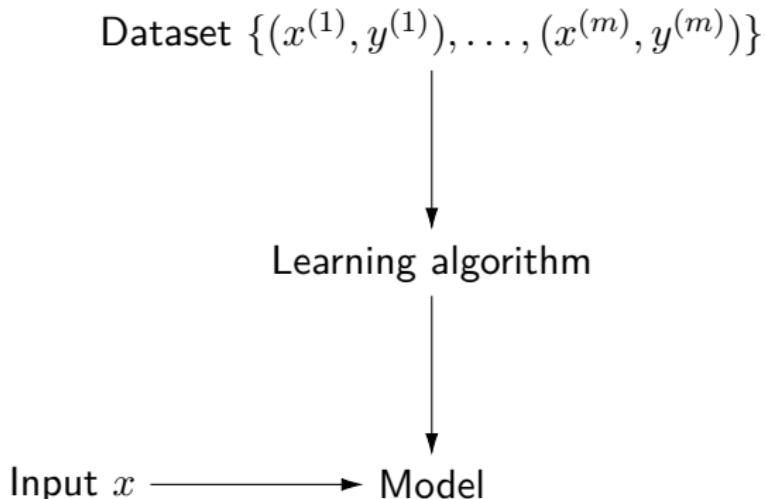
Machine Learning



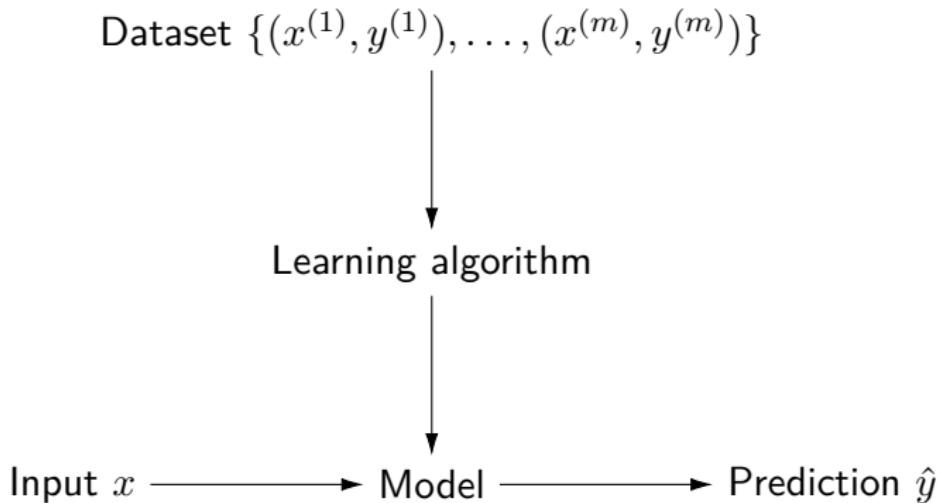
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Machine Learning



Machine Learning

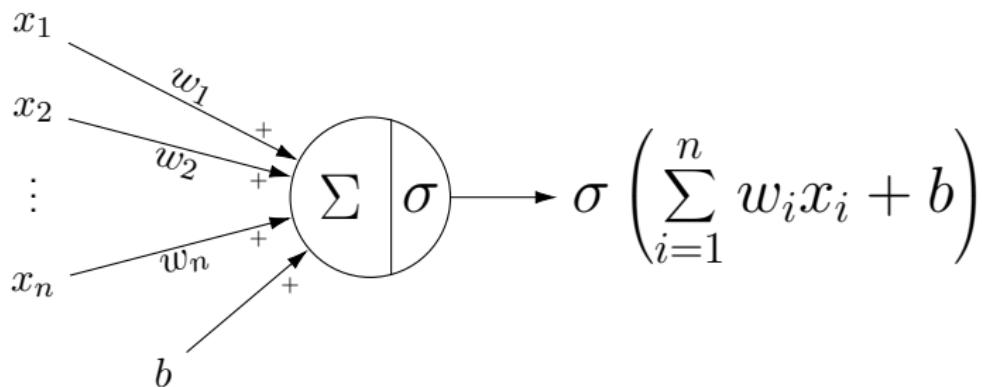


The Basis of Neural Networks: The Neuron

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

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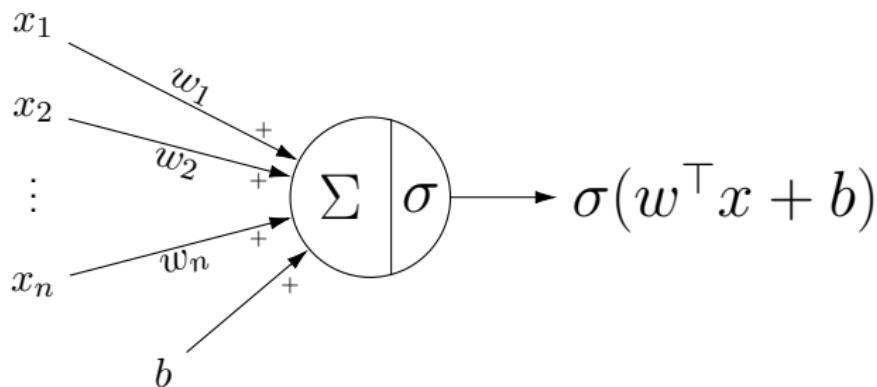
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A neuron computes the following.



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

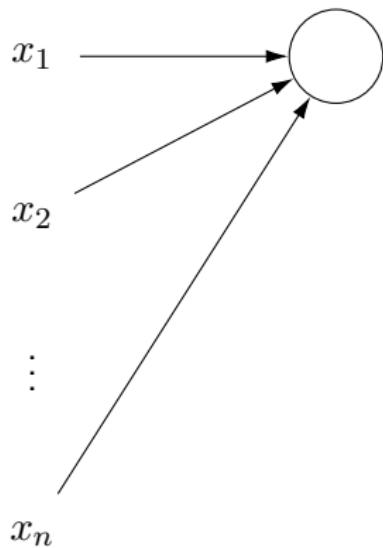
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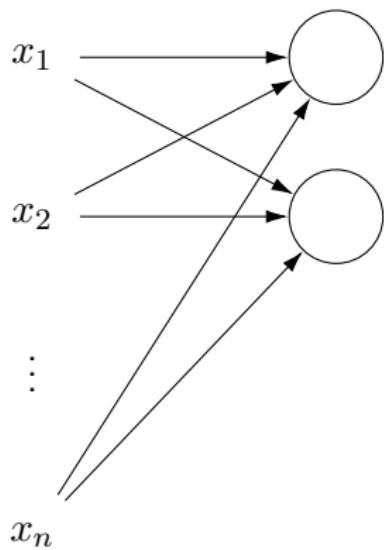
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Neural Network



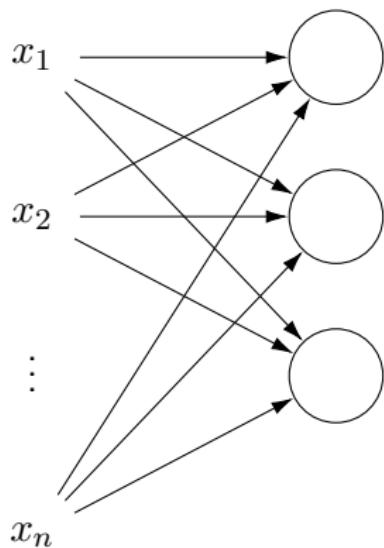
$$y = f_L \circ f_{L-1} \circ \dots \circ f_2 \circ f_1(x), \quad f_\ell = \sigma(W_{\ell-1}f_{\ell-1} + b_{\ell-1}), \\ f_0 = Id(x)$$

Neural Network



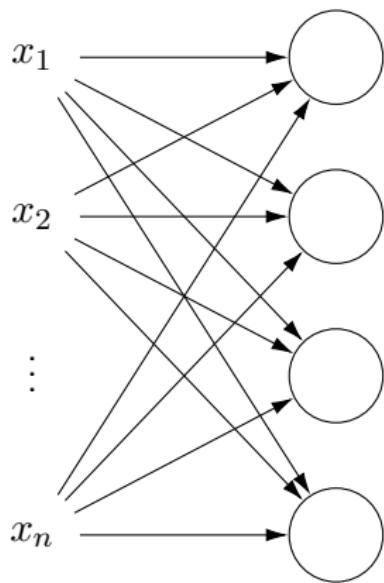
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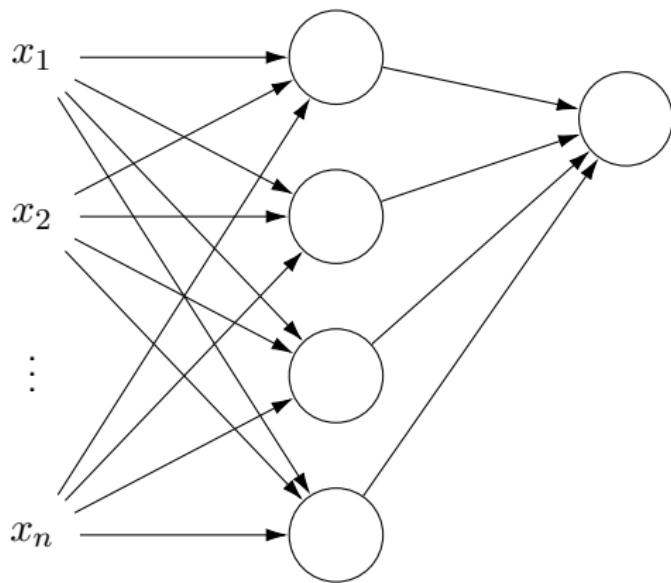
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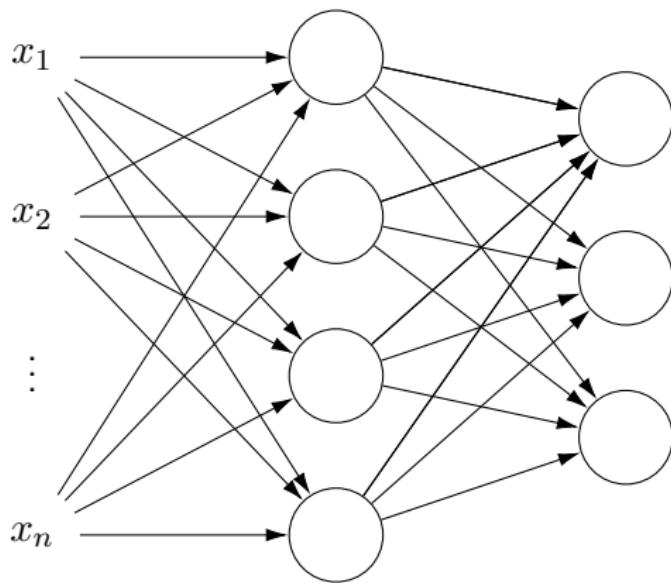
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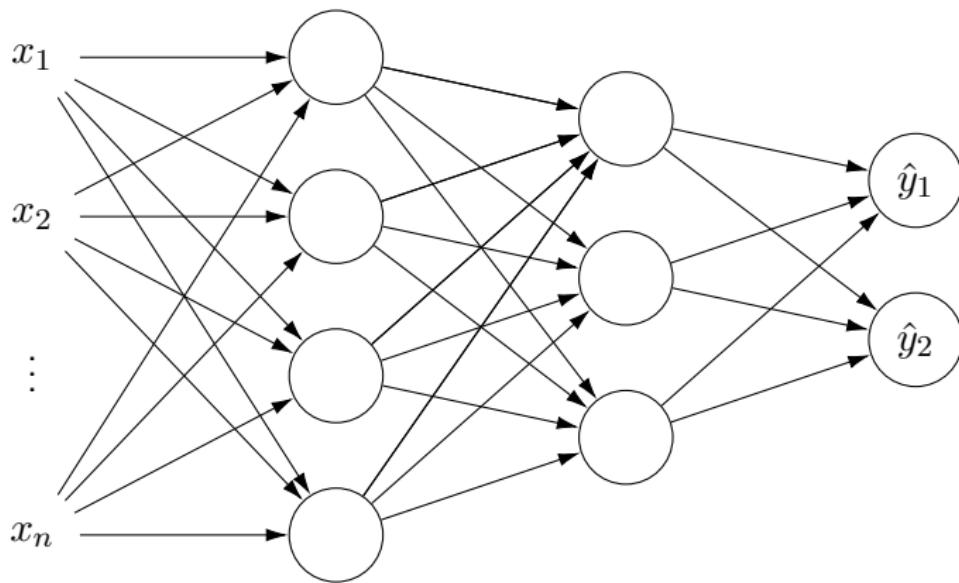
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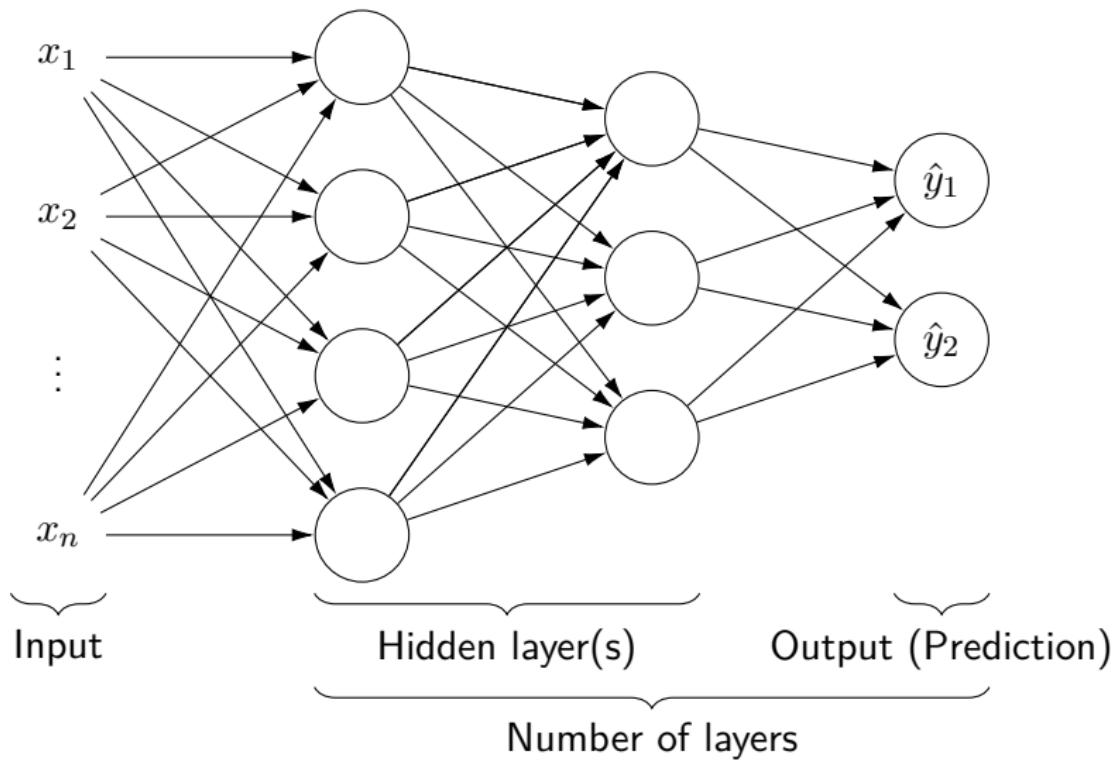
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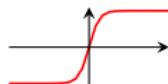
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Given a non-activated output $z = w^\top x + b$, then $\sigma(z) = \dots$

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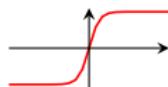
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Activation Functions

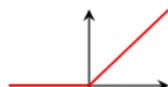
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- The ReLU function:

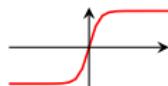
$$\text{ReLU}(z) = \max(0, z)$$



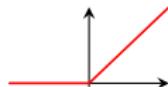
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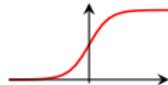


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- The logistic function (also called sigmoid function):

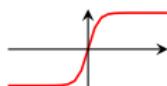
$$\sigma(z) = \frac{1}{1 + \exp(-z)}$$



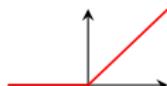
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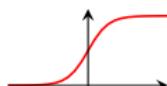
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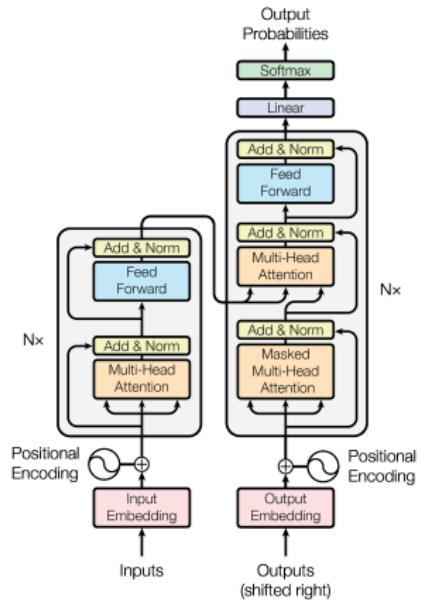
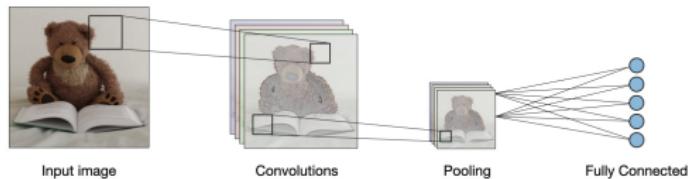


- The softmax function:

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

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

Other Architectures



Loss Function

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

Goal: minimize the loss function!

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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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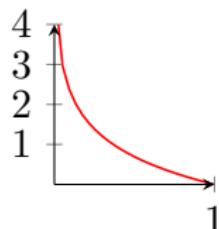
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Training Objective

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

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

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

Training Objective

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

- The only thing we control are the parameters θ .

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

Training Objective

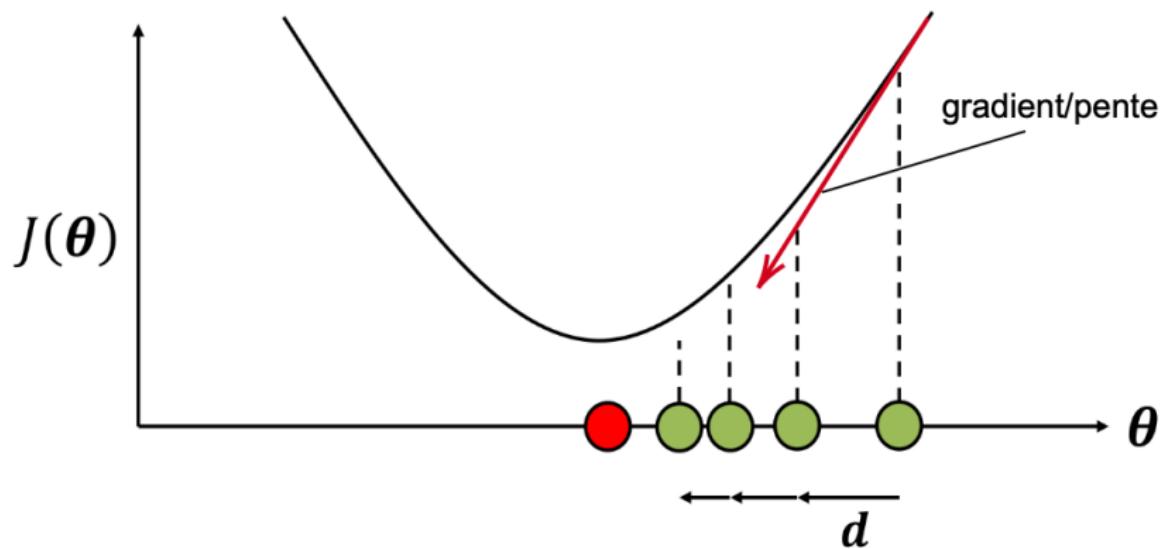
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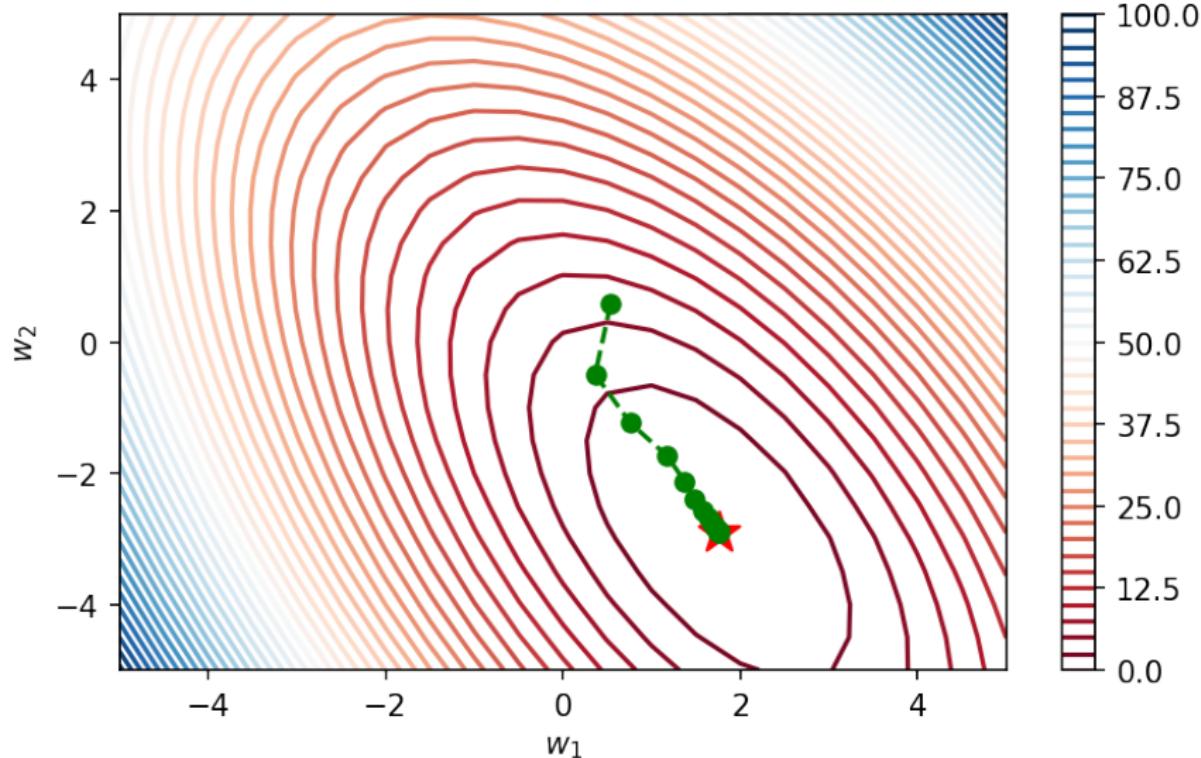
$$\theta^* = \operatorname{argmin}_{\theta \in \Theta} J(\theta)$$

Gradient Descent

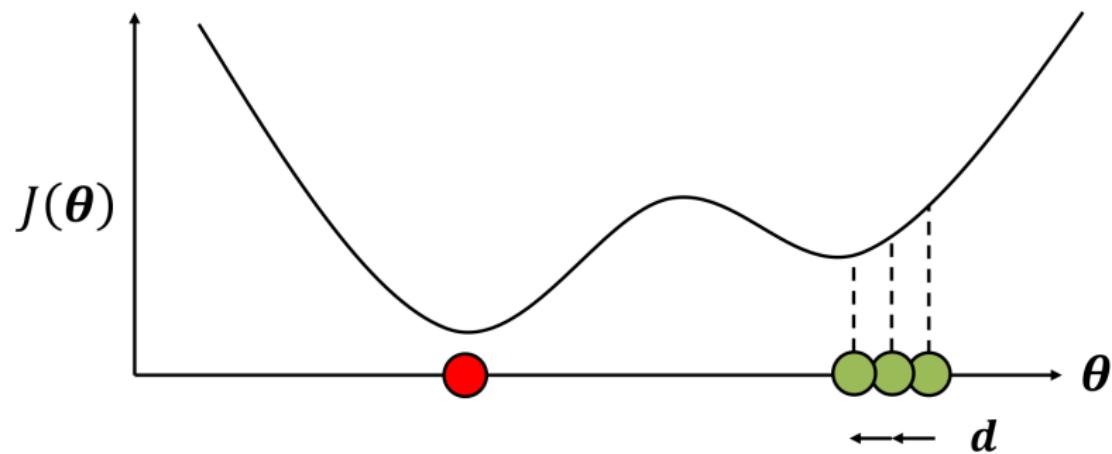


From Université Laval GLO-7030 by Ludovic Trottier

Gradient Descent



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



Computation of Gradient

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

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

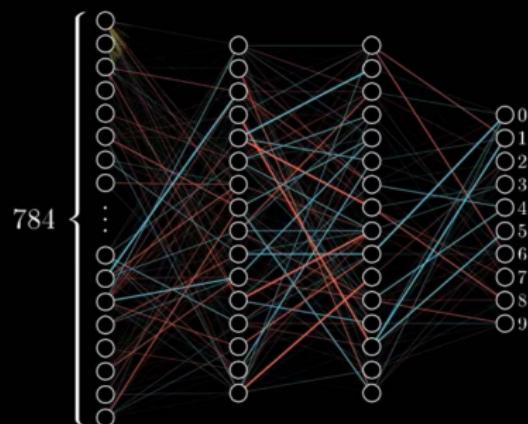
To update the parameters:

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

ϵ is called the learning rate.

Gradient

Training in
progress. . .



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

Optimization Algorithms

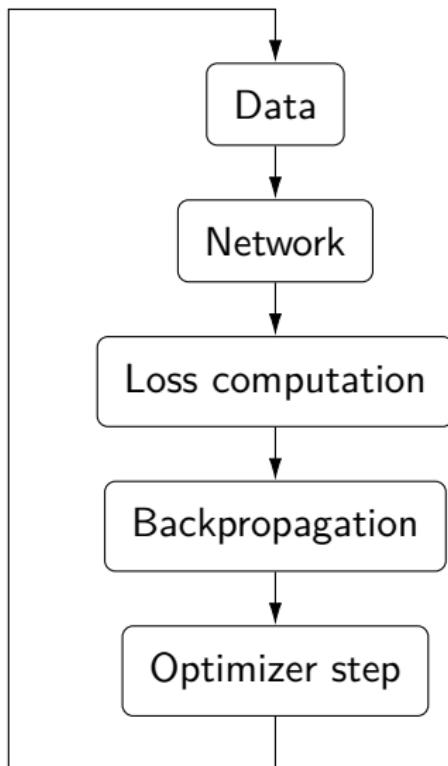
Simplest update rule:

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

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

Training Procedure

```
procedure TRAIN( $f(\cdot; \theta)$ ,  $S$ )
    input: Neural network  $f$  parameterized by  $\theta$ 
    input: Dataset  $S = \{(x_1, y_1), \dots, (x_N, y_N)\}$ 
    for  $n$  epochs do
        end for
end procedure
```

Training Procedure

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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.

end while

end for

end procedure

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

 Update θ with d using chosen optimizer

end while

end for

end procedure

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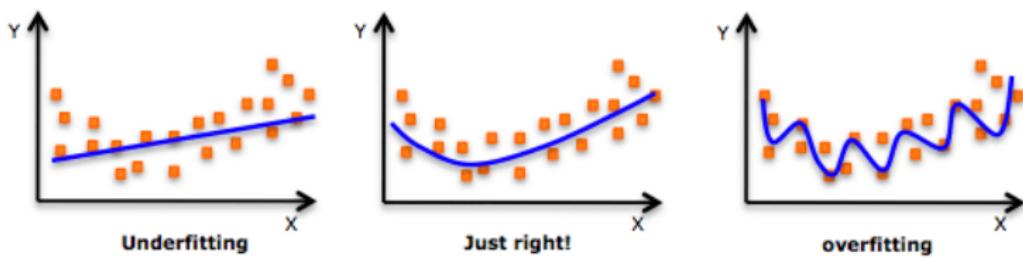
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Neural Networks are Powerful

- Universal Approximation Theorem

Neural Networks are Powerful

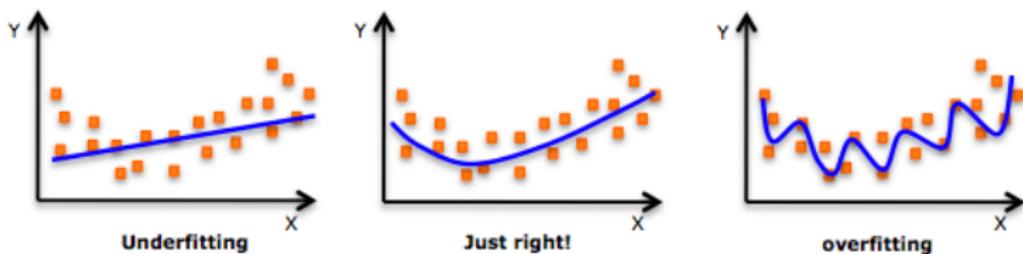
- Universal Approximation Theorem
- ... is a *blessing!*



An example of overfitting, underfitting and a model that's "just right!"

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- ... is a *blessing*!
- ... and a *curse*!
- How can we avoid overfitting?

Regularization

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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- L1 regularization (or LASSO): $\Omega(f) = \|\theta\|_1$

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- L1 regularization (or LASSO): $\Omega(f) = \|\theta\|_1$
- etc.

¹MLE stands for Maximum Likelihood Estimation.

Dropout

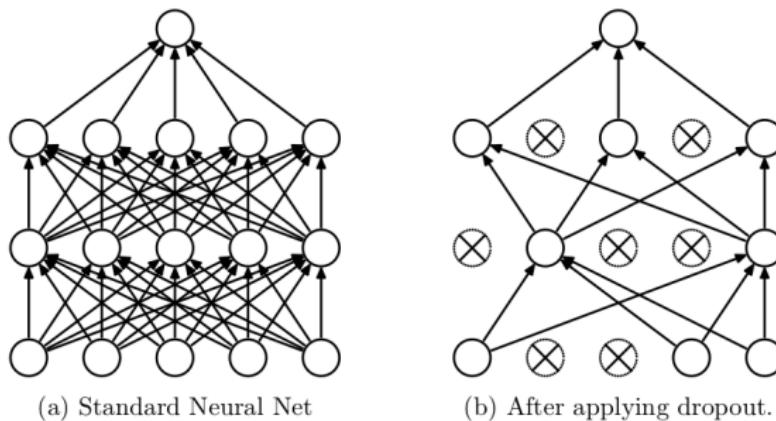
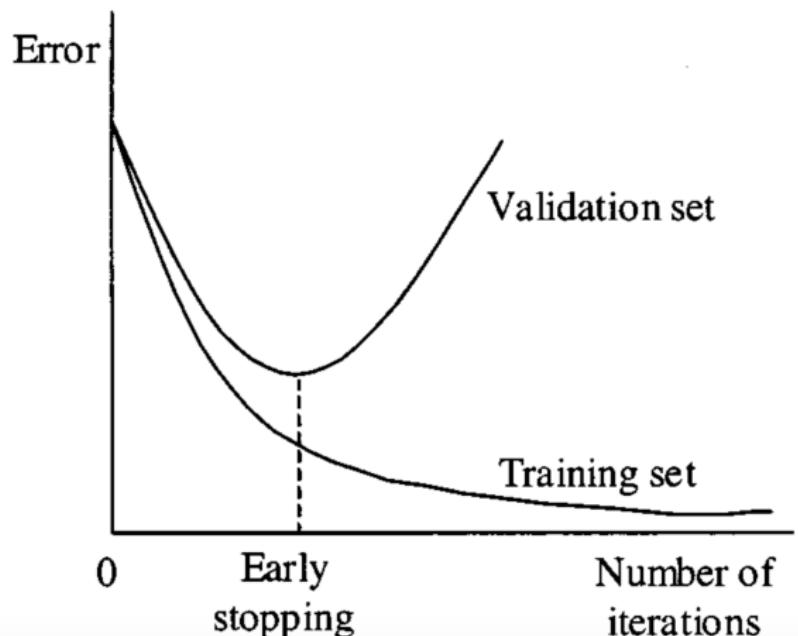


Figure 1: Dropout Neural Net Model. **Left:** A standard neural net with 2 hidden layers. **Right:** An example of a thinned net produced by applying dropout to the network on the left. Crossed units have been dropped.

Early Stopping

Extract a validation set \mathcal{V} from the training set. Use it to assess generalization potential.



More ways to regularize

- Control the model capacity (e.g.:depth)
- More Data
- Data Augmentation

Deep Learning Libraries



TensorFlow

Deep Learning Libraries



TensorFlow



PyTorch 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>
- Blogpost: A Recipe for Training Neural Networks. Andrej Karpathy
- 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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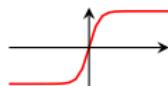
Activation Functions

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

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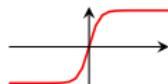
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Activation Functions

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- The ReLU function:

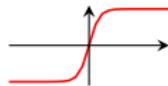
$$\text{ReLU}(z) = \max(0, z)$$



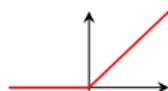
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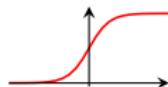


- The ReLU function:



- The logistic function (also called sigmoid function):

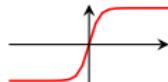
$$\sigma(z) = \frac{1}{1 + \exp(-z)}$$



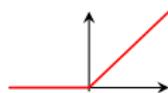
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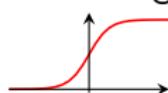
- $\tanh(z)$



- The ReLU function:



- The logistic function (also called sigmoid function):



- The softmax function:

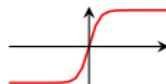
$$\text{softmax}(z)_i = \frac{\exp(z_i)}{\sum_{j=1}^m \exp(z_j)}$$

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

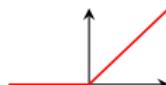
Activation Functions

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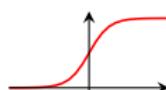
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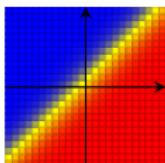
- The ReLU function:



- 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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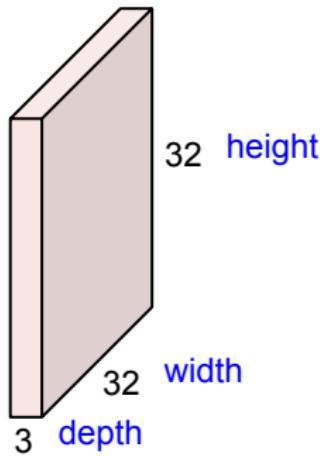
Based on the cross entropy:

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

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

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

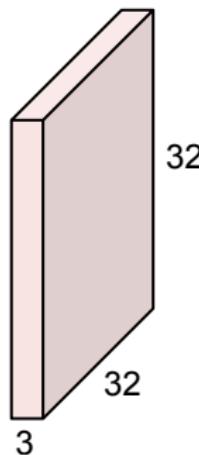
Convolution Layer



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

Convolution Layer

32x32x3 image

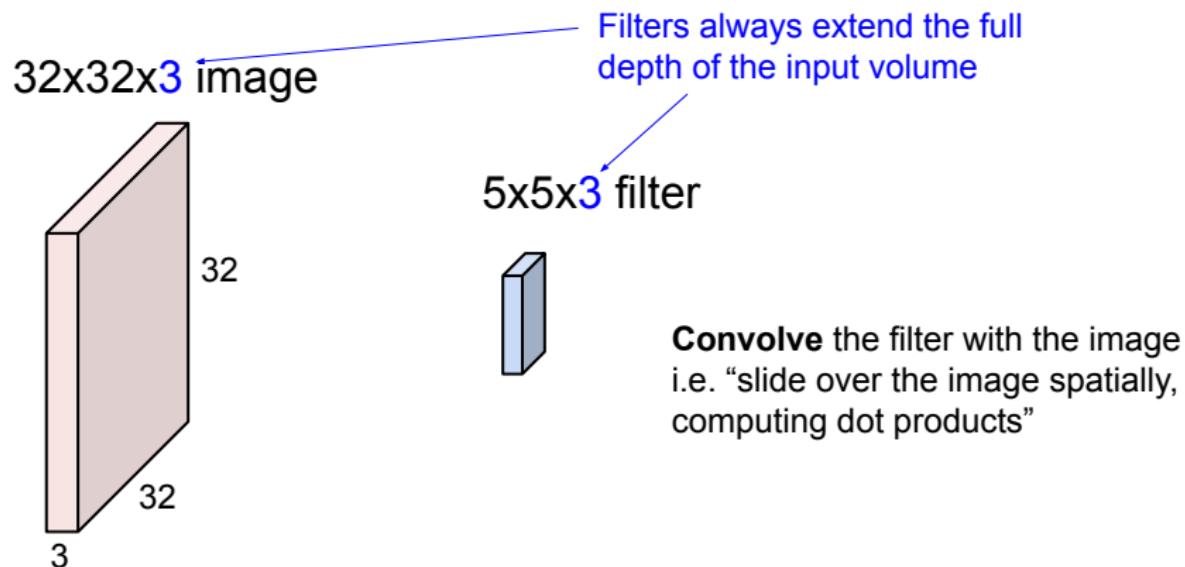


5x5x3 filter

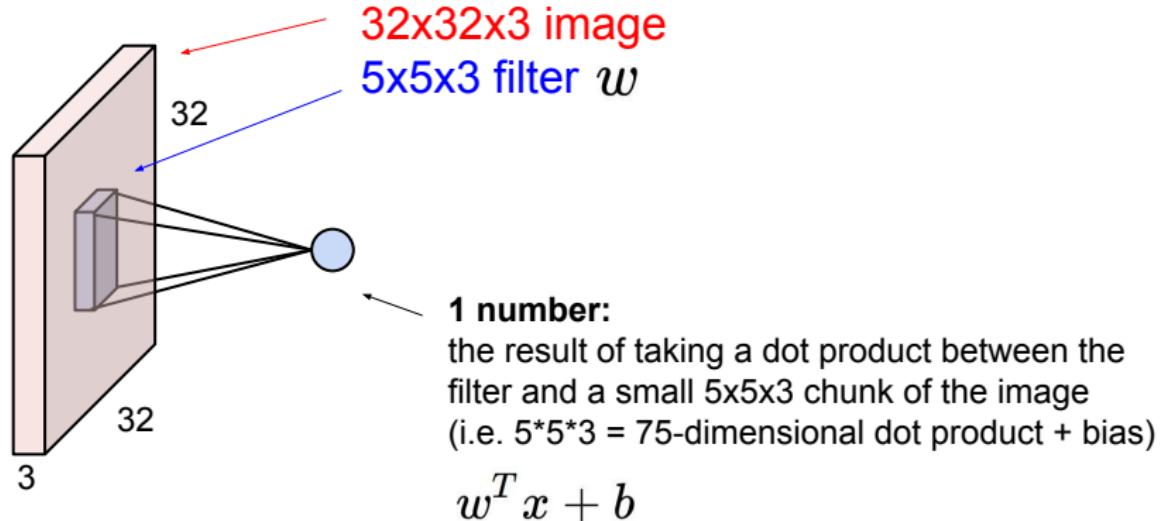


Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Convolution Layer

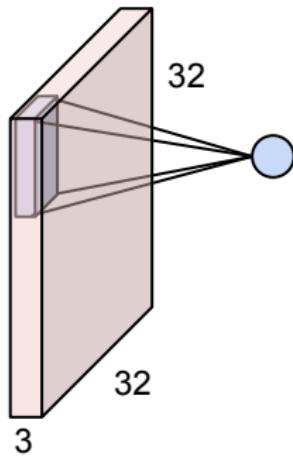


Convolution Layer



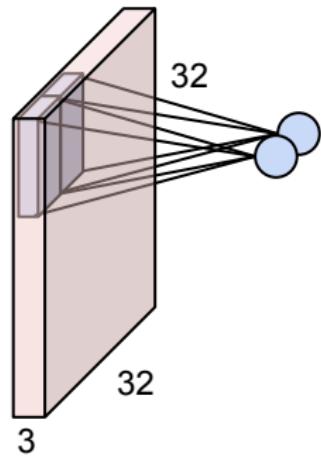
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Convolution Layer



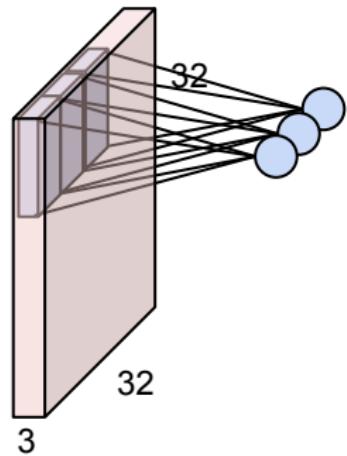
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Convolution Layer



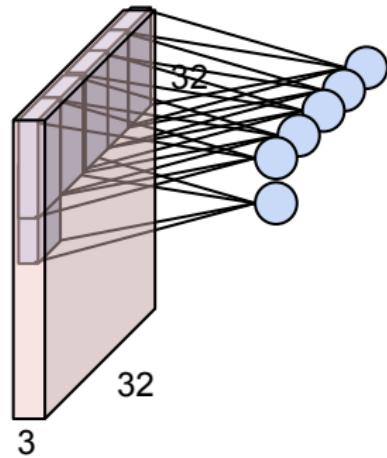
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Convolution Layer



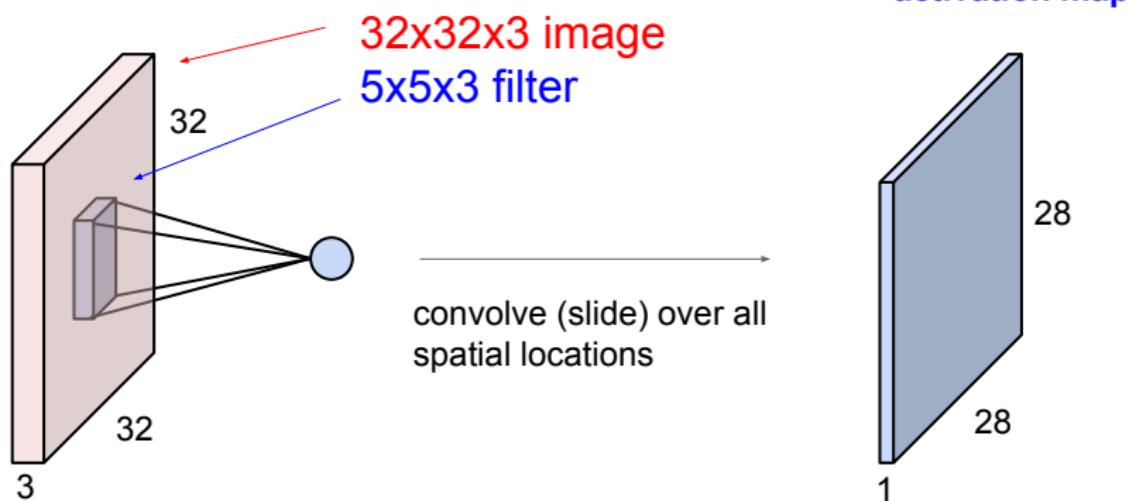
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Convolution Layer



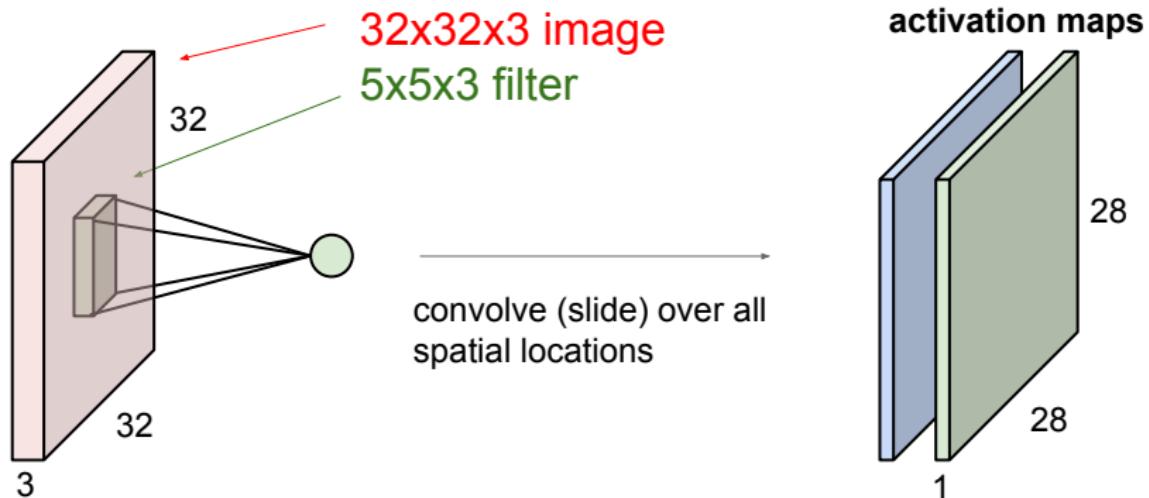
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Convolution Layer



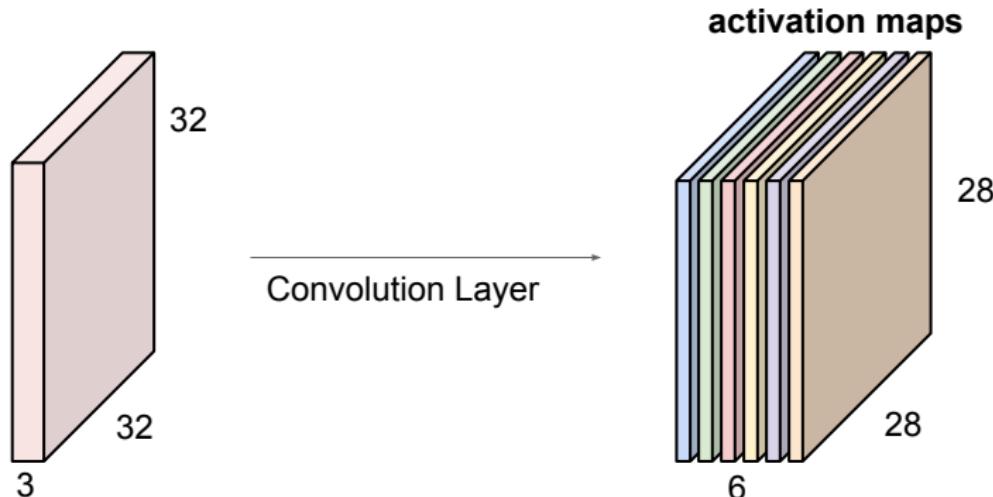
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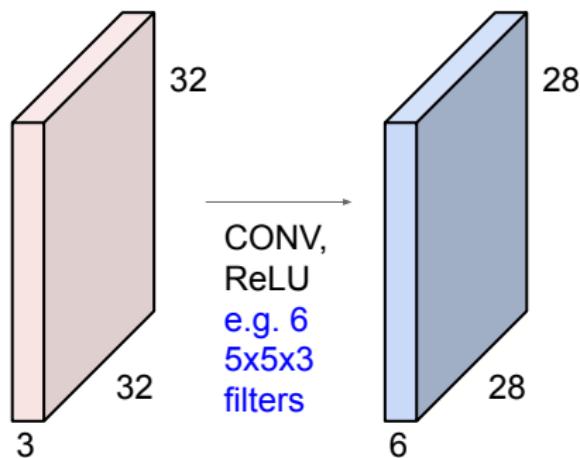
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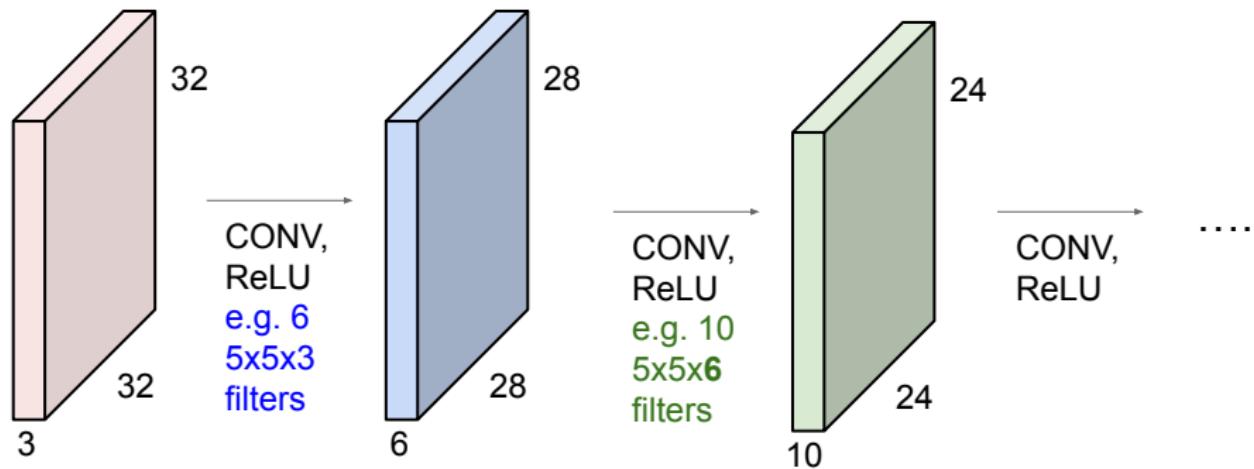
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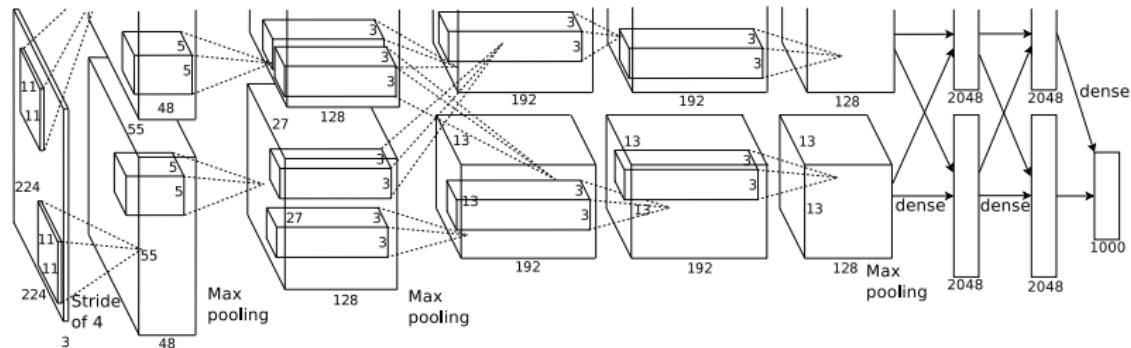
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Other Types of Layers

Many types of layers exist. Here is a few.

- Max pooling/average pooling
- Batch normalization
- Dropout

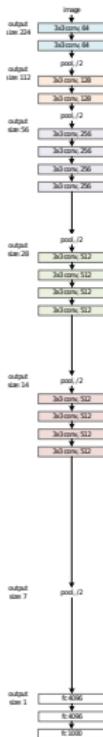
Deep Neural Network Architectures



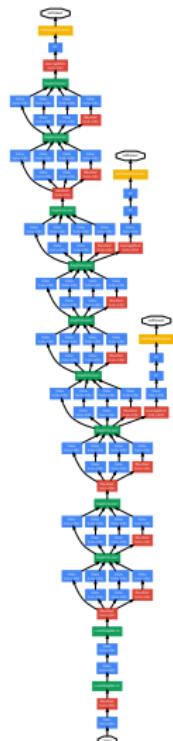
AlexNet

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

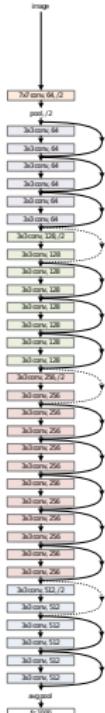
Deep Neural Network Architectures



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"]