Introduction to Deep Learning

Bootcamp IID 2024

Jonas Ngnawé

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Institut intelligence et données

Group for Research in Artificial Intelligence of Laval University

UNIVERSITÉ LAVAL

Who Am I?

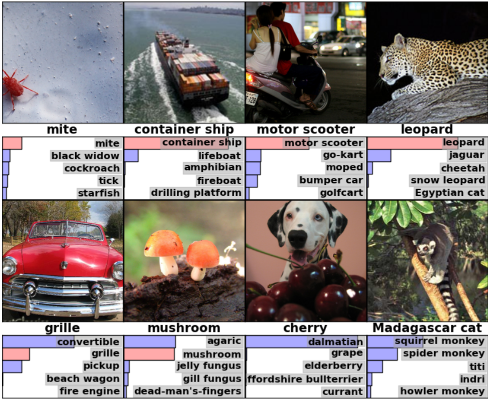
Jonas Ngnawé

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

jonas-ngnawe-bb7712a2

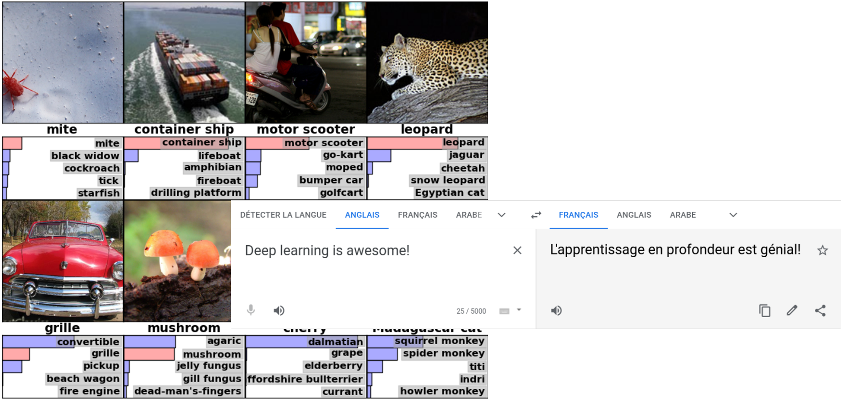
Slides Credit: Frédérik Paradis, Mathieu Godbout et Alexandre Bouras

Deep Neural Networks



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

Deep Neural Networks

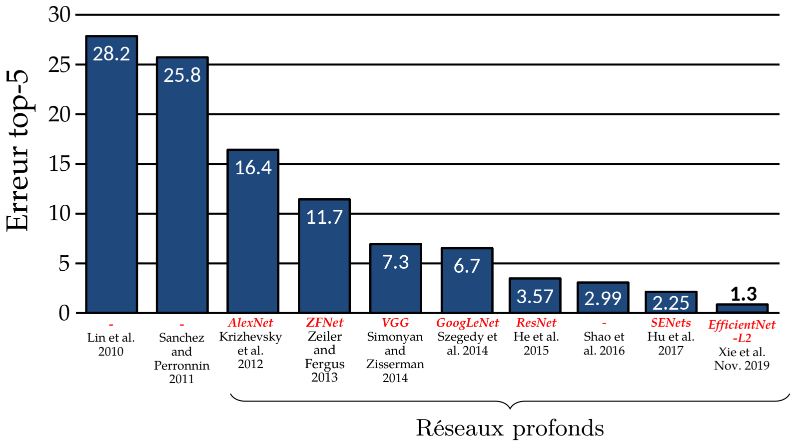


[Krizhevsky et al. 2012, "ImageNet Classification with Deep Convolutional Neural Networks"]

Computer Vision

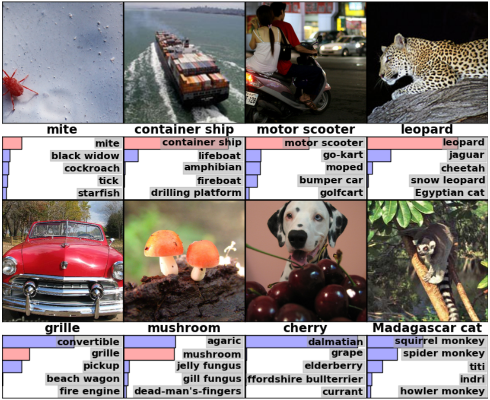
Large Scale Visual Recognition Challenge (LSVRC)

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



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

- Image classification



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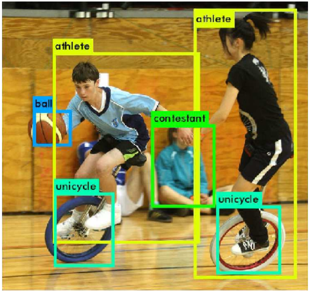
Computer Vision

- 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"]

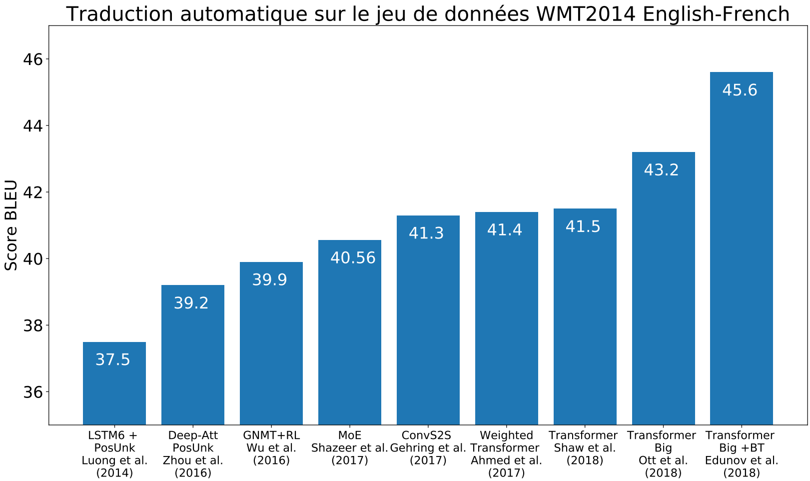
Computer Vision

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

Computer Vision

- Image classification
- Object detection
- Image segmentation
- Image generation
- etc.

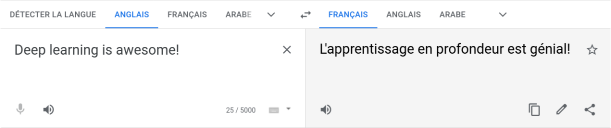
Natural Language Processing (NLP)



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

Natural Language Processing

- Translation



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

Natural Language Processing

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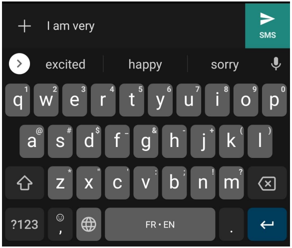

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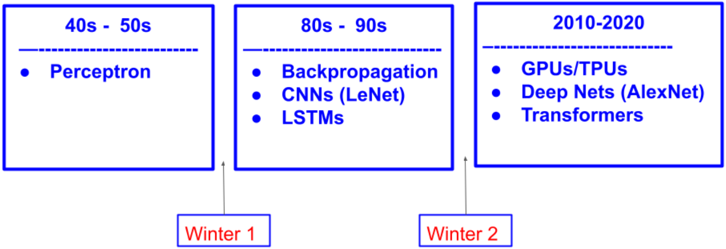
History Overview



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

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Learning algorithm

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Model

Machine Learning

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

Learning algorithm

Input x $\longrightarrow$ Model

Machine Learning

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

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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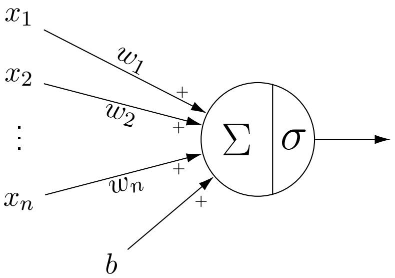
A neuron computes the following.



$$\sigma\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

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

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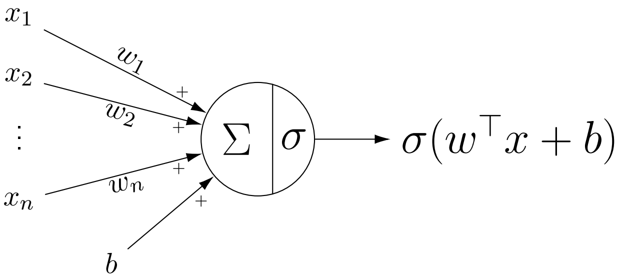

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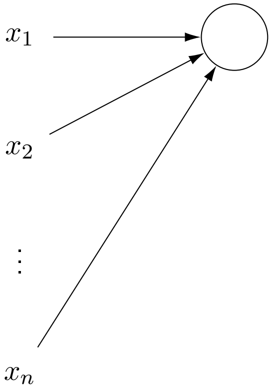
Neural Network



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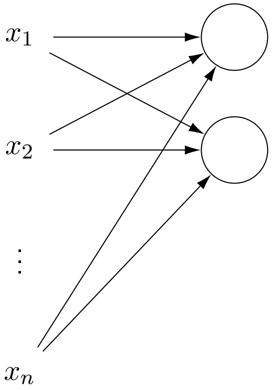

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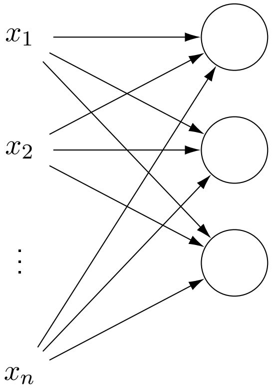

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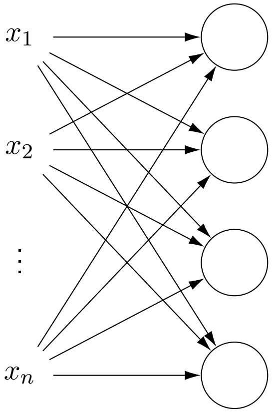

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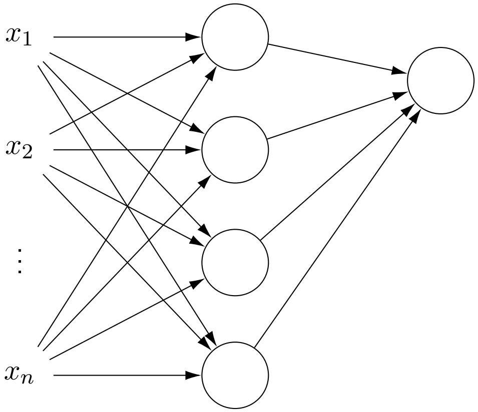

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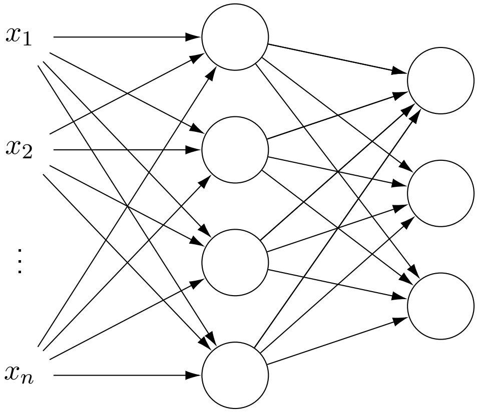

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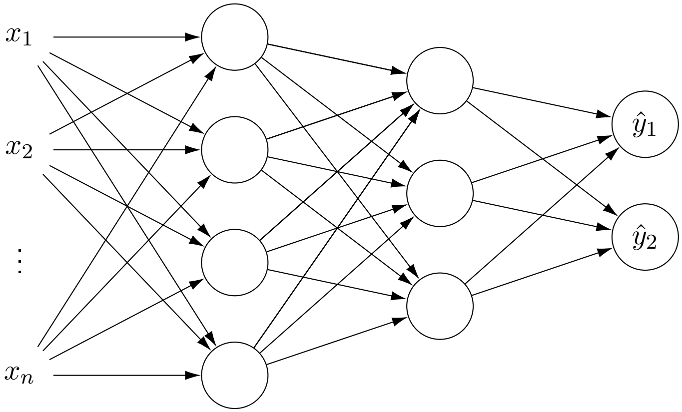

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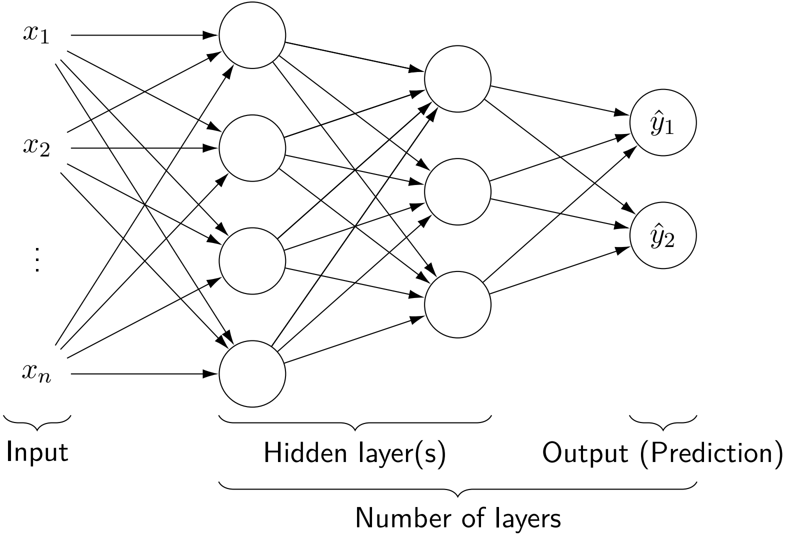

$$y = f_L \circ f_{L-1} \circ \ldots \circ f_2 \circ f_1(x),\ f_\ell = \sigma(W_\ell f_{\ell-1} + b_\ell),\ f_0 = x$$

Activation Functions

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

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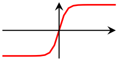

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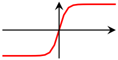
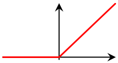


- The ReLU function:

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



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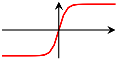

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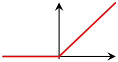
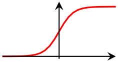


- The logistic function (also called sigmoid function):

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



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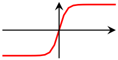

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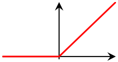

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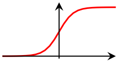
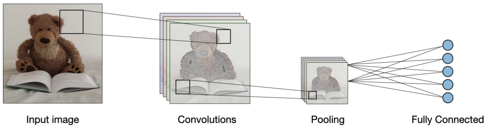


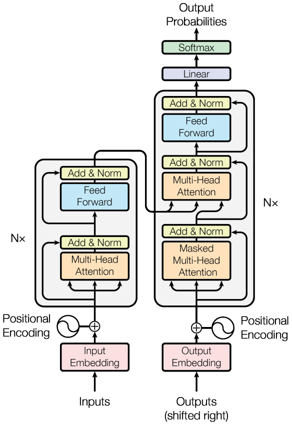
- The softmax function:

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

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

Other Architectures





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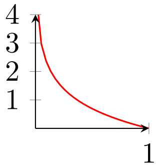

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$$\mathcal{L}(f(x), y)$$

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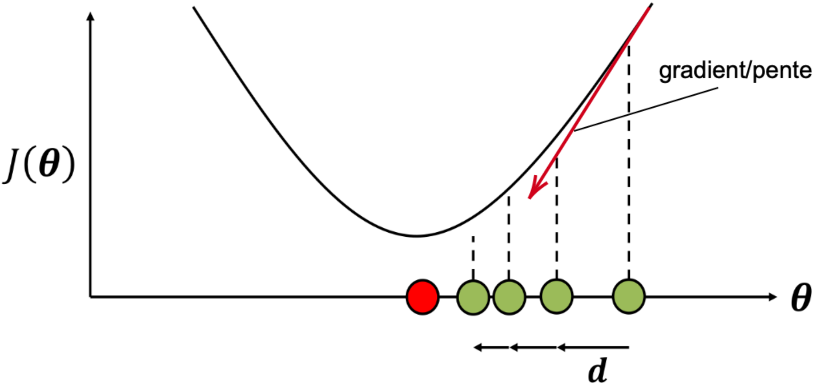
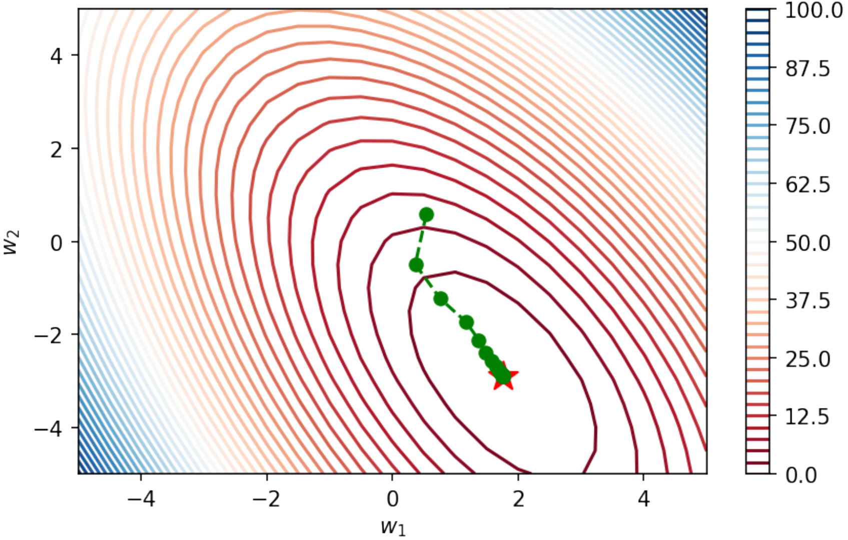
$$
\theta^* = \operatorname*{argmin}_{\theta\in\Theta} J(\theta)
$$

Gradient Descent



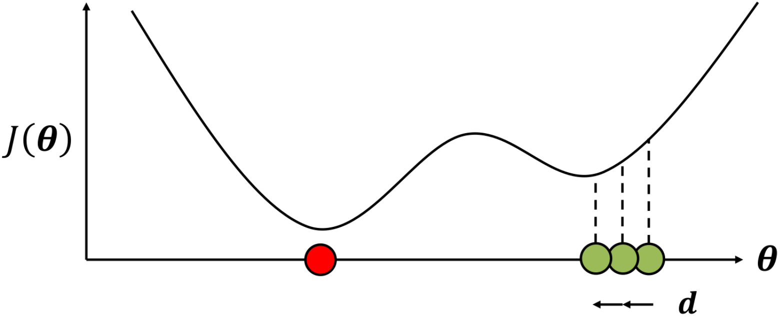
From Université Laval GLO-7030 by Ludovic Trottier

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 **the loss** with respect to **each parameter**. The vector containing all partial derivatives is called the **gradient**.

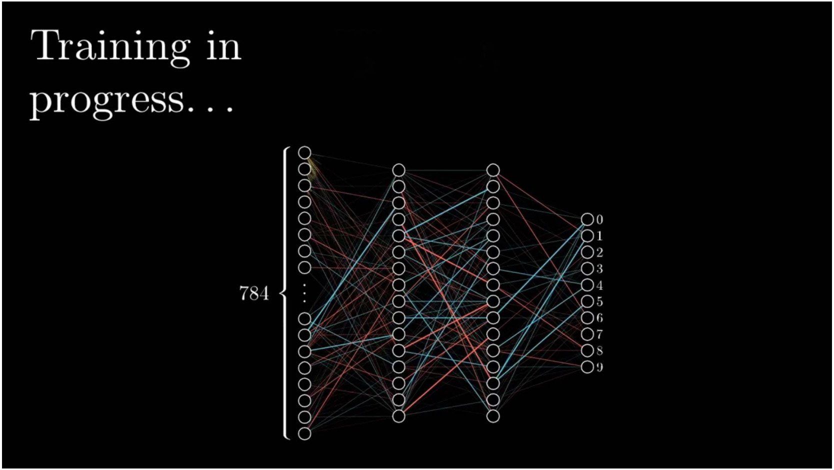
$$d = \nabla_\theta J(\theta) = \left[\frac{\partial J(\theta)}{\partial \theta_1}, \ldots, \frac{\partial J(\theta)}{\partial \theta_n}\right]$$

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

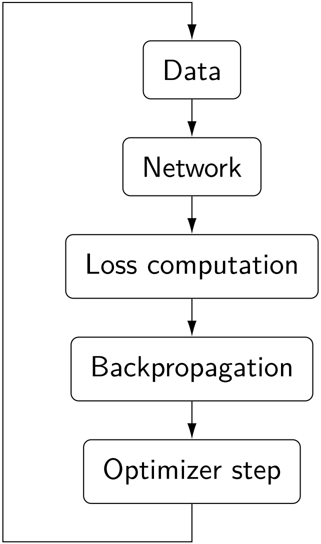
Simplest update rule:

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

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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        Let $S' = S$
        while $S' \neq \emptyset$ **do**
            Draw a batch $B \subseteq S'$ of b examples.
        end while
    end for
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      $d = \nabla_\theta \ell$

      Update θ with d using chosen optimizer

    end while

  end for

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Neural Networks are Powerful

- Universal Approximation Theorem

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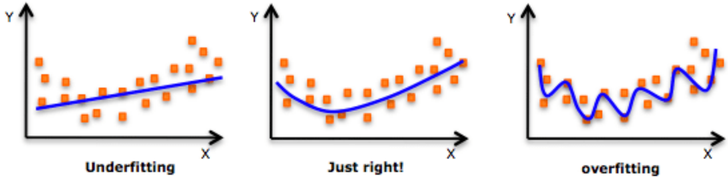
- ... is a *blessing*!



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

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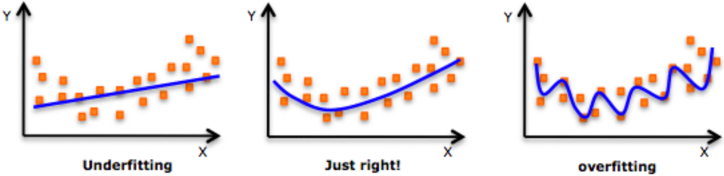

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- ... is a *blessing*!
- ... and a *curse*!
- How can we avoid overfitting?

Regularization

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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- L2 regularization: $\Omega(f) = \|\theta\|_2^2$, where θ are the learneable parameters of the neural network f.
- L1 regularization (or LASSO): $\Omega(f) = \|\theta\|_1$

[1] MLE stands for Maximum Likehood Estimation.

Regularization

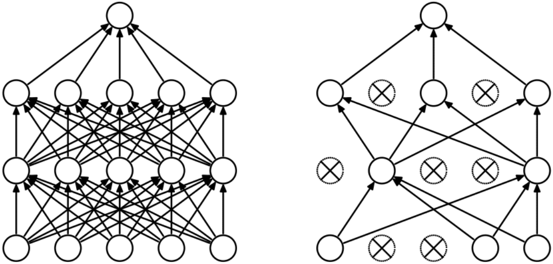
Add a penalty term to the loss[1]:

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

- L2 regularization: $\Omega(f) = \|\theta\|_2^2$, where θ are the learneable parameters of the neural network f.
- L1 regularization (or LASSO): $\Omega(f) = \|\theta\|_1$
- etc.

[1] MLE stands for Maximum Likehood Estimation.

Dropout

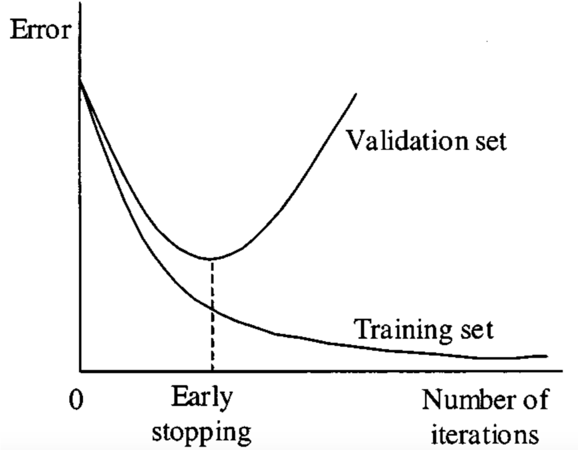


(a) Standard Neural Net (b) After applying dropout.

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

PyTorch

Deep Learning Libraries

TensorFlow

PyTorch

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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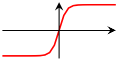
Activation Functions

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

Activation Functions

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

- $\tanh(z)$



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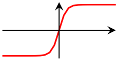
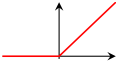


- The ReLU function:

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



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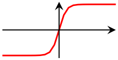

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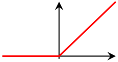
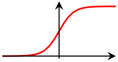


- The logistic function (also called sigmoid function):

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



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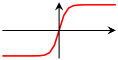

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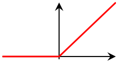

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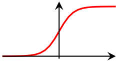


- The softmax function:

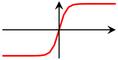
$$\mathsf{softmax}\,(z)_i = \frac{\exp(z_i)}{\sum_{j=1}^{m} \exp(z_j)}$$

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

Activation Functions

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

- $\tanh(z)$



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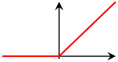

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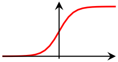

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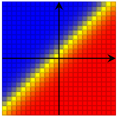

$\boxed{\text{softmax}\,(z)_1 = \frac{\exp(x)}{\exp(x)+\exp(y)} \text{ for } z = [x, y]}$

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:

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

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

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  - $\hat{y} = [\hat{y}_1, \ldots, \hat{y}_C] = \mathsf{softmax}\left([z_1, \ldots, z_C]\right)$

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  Based on the cross entropy:

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

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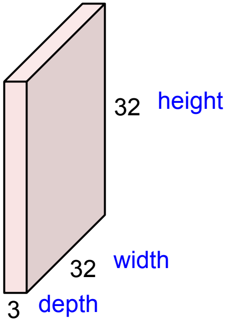
  Based on the cross entropy:

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

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

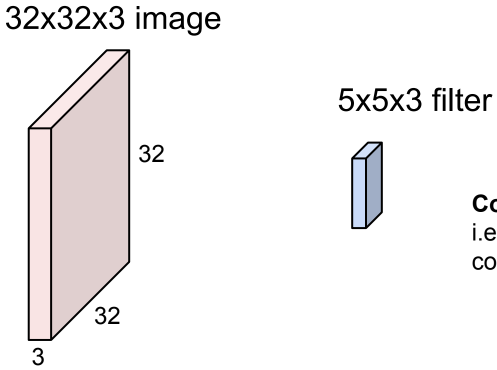
$$\mathcal{L}_{\mathsf{CE}}(\hat{y}, y) = -\sum_{c=1}^{C} \mathbb{1}(y = c) \log \hat{y}_c = -\log \hat{y}_y$$

Convolution Layer



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

Convolution Layer

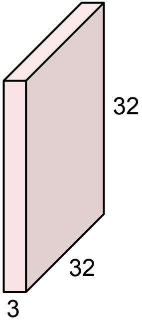


Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

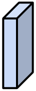
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Filters always extend the full depth of the input volume

32x32x3 image



5x5x3 filter



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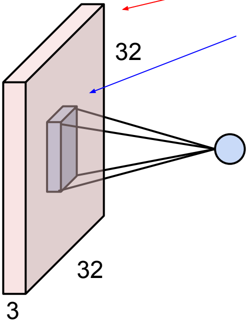
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Convolution Layer



32x32x3 image

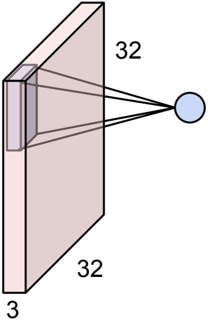
5x5x3 filter w

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



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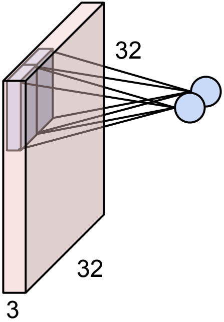

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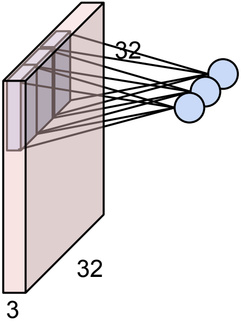

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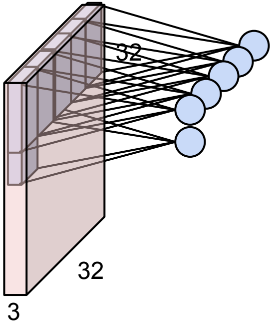

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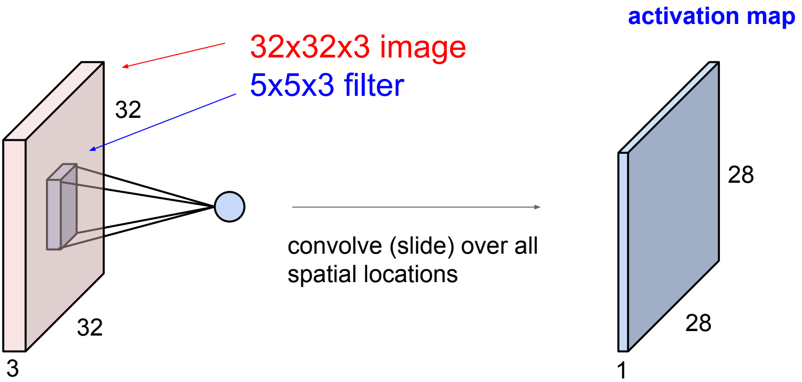
Convolution Layer



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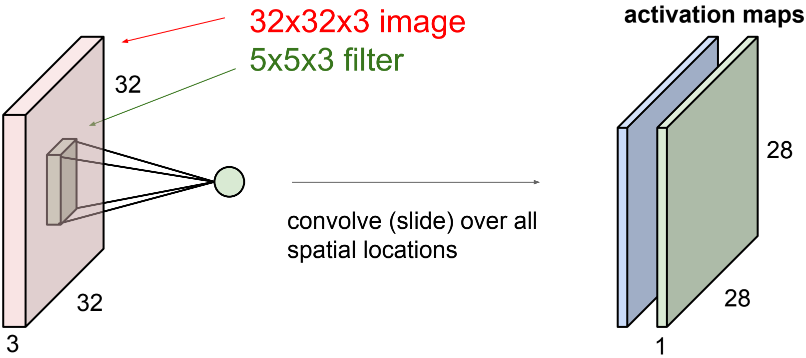

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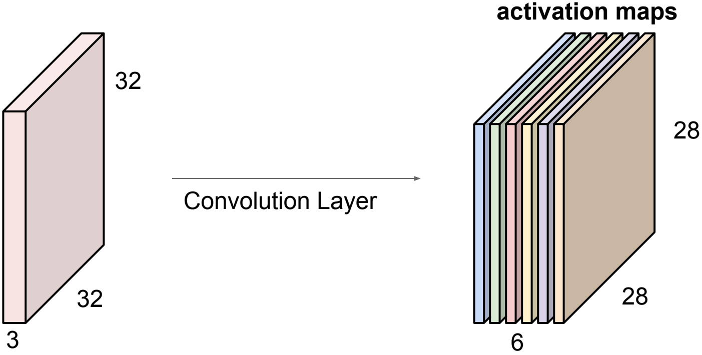

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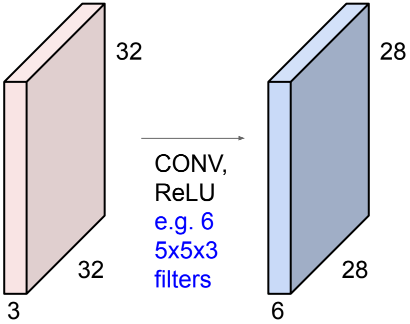
Convolution Layer



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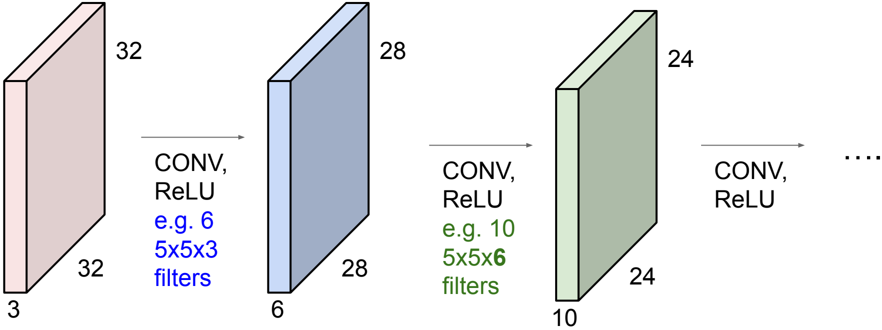


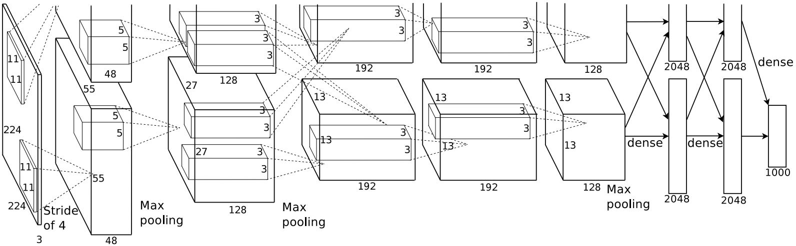
Slides of Fei-Fei Li, Ranjay Krishna, Danfei Xu; Standford CS231n.

Other Types of Layers

Many types of layers exist. Here is a few.

- Max pooling/averge pooling
- Batch normalization
- Dropout

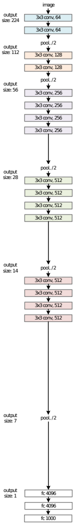
Deep Neural Network Architectures



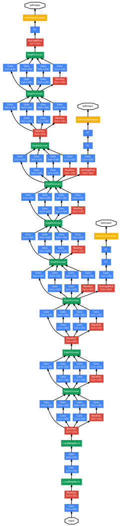
AlexNet

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

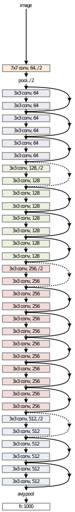
Deep Neural Network Architectures



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"]