Class 13: CNNs and Image Classification

Theme: Images

Computational Analysis of Text, Audio, and Images, Fall 2023

Aarhus University

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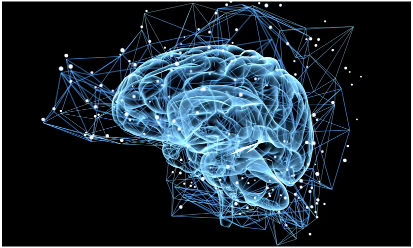
- Neurons are connected to each other and propagate signals to one another



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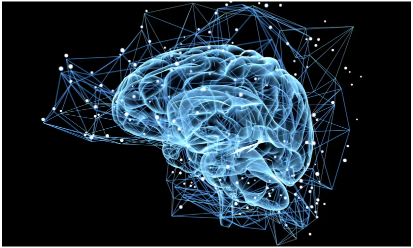

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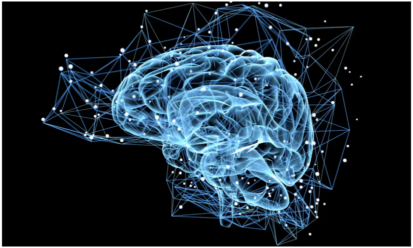

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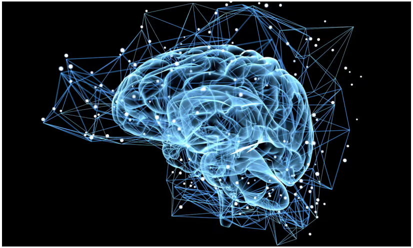

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⇝ This whole idea is encoded in artificial neural networks (ANNs)

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- In theory: NNs $\neq$ deep learning
- In practice: NNs $=$ deep learning

NN Components

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- Activations
- Parameters (weights and biases)
- Layers

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How can we explain each of the components?

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where:

- w_0 is the bias/intercept (also called b_0)
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In math, this is called a linear combination

Graph Regression

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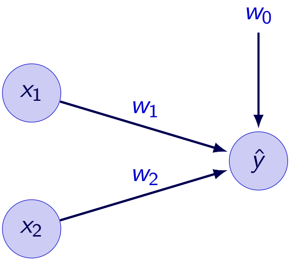

$$= z_1 = w_0 + w_1 x_1 + w_2 x_2 = \begin{cases} 0 & \text{if } z_1 \leq 0 \\ 1 & \text{if } z_1 > 0 \end{cases}$$

Non-Linearity

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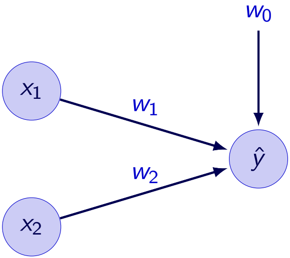

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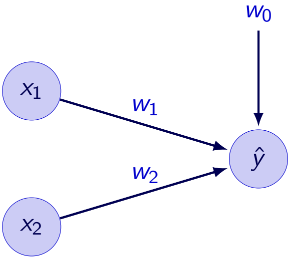

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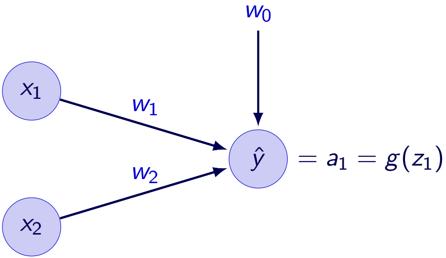

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$\rightsquigarrow$ without activation functions, NNs are limited to solving linear problems

Activation Functions

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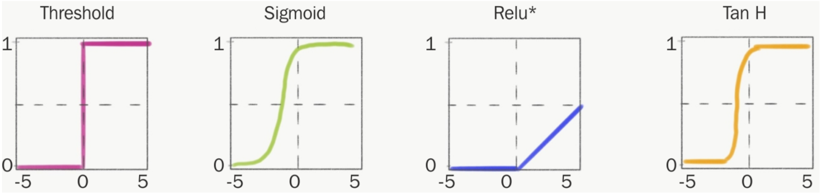

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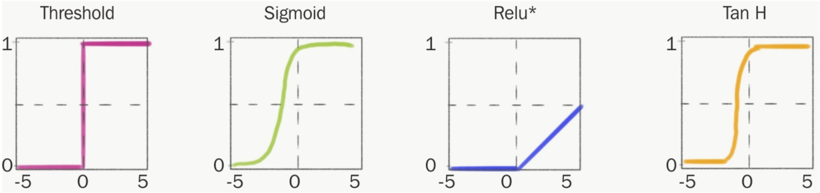

$$\text{Step Function:} \quad f(x) = \begin{cases} 0, & \text{if } x < 0 \\ 1, & \text{if } x \geq 0 \end{cases}$$

$$\text{Sigmoid:} \quad f(x) = \frac{1}{1 + e^{-x}}$$

$$\text{ReLU (Rectified Linear Unit):} \quad f(x) = \max(0, x)$$

$$\text{tanh:} \quad f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

A Vanilla NN

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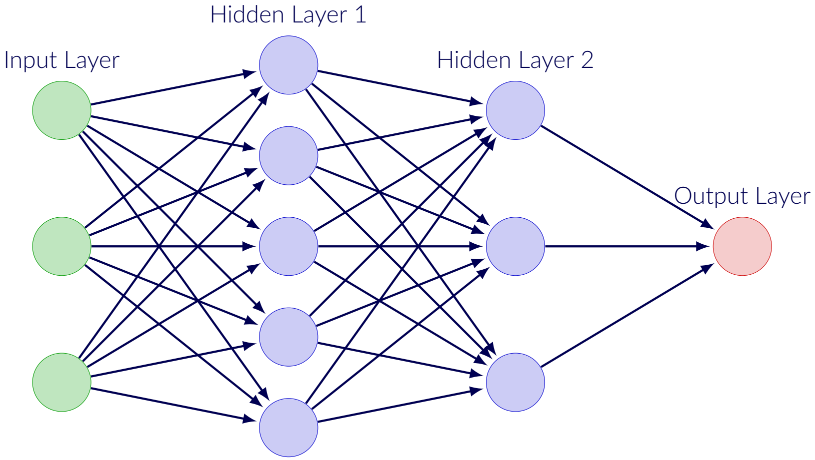

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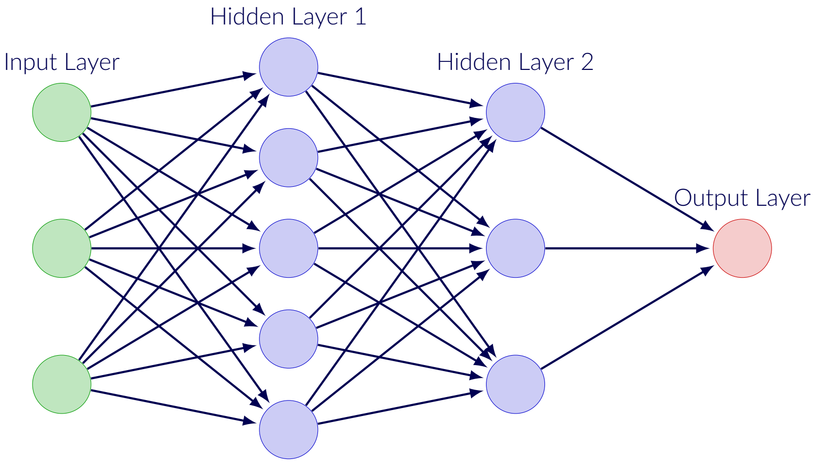

1. How many neurons do the network contains?
2. How many layers?
3. How many weights and biases?

Forward and Backward Passing

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- Backward pass: Compute partial derivatives

NN Notation

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In this notation, we can write the relations between a hidden neuron j in layer L and the previous layer $L-1$ as:

$$z_j^{(L)} = \sum_k w_{jk}^{(L)} a_k^{(L-1)} + b_j^{(L)} \tag{1}$$

$$a_j^{(L)} = g\left(z_j^{(L)}\right) \tag{2}$$

where g is an activation function.

Nested Regressions

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$$w^{(L)} = \begin{bmatrix} w_{11}^{(L)} & w_{12}^{(L)} & w_{13}^{(L)} & w_{14}^{(L)} & w_{15}^{(L)} \\ w_{21}^{(L)} & w_{22}^{(L)} & w_{23}^{(L)} & w_{24}^{(L)} & w_{25}^{(L)} \\ w_{31}^{(L)} & w_{32}^{(L)} & w_{33}^{(L)} & w_{34}^{(L)} & w_{35}^{(L)} \end{bmatrix}' \quad b^{(L)} = \begin{bmatrix} b_1^{(L)} \\ b_2^{(L)} \\ b_3^{(L)} \end{bmatrix} \quad a^{(L-1)} = \begin{bmatrix} a_1^{(L-1)} \\ a_2^{(L-1)} \\ a_3^{(L-1)} \\ a_4^{(L-1)} \\ a_5^{(L-1)} \end{bmatrix}$$

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What's the output dimension when we compute the product $w^{(L)}a^{(L-1)}$?

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$$\begin{aligned}
z_1^{(L)} &= w_{11}^{(L)} a_1^{(L-1)} + w_{12}^{(L)} a_2^{(L-1)} + w_{13}^{(L)} a_3^{(L-1)} + w_{14}^{(L)} a_4^{(L-1)} + w_{15}^{(L)} a_5^{(L-1)} + b_1^{(L)} \\
&= \sum_k w_{1k}^{(L)} a_k^{(L-1)} + b_1^{(L)} \\
z_2^{(L)} &= w_{21}^{(L)} a_1^{(L-1)} + w_{22}^{(L)} a_2^{(L-1)} + w_{23}^{(L)} a_3^{(L-1)} + w_{24}^{(L)} a_4^{(L-1)} + w_{25}^{(L)} a_5^{(L-1)} + b_2^{(L)} \\
&= \sum_k w_{2k}^{(L)} a_k^{(L-1)} + b_2^{(L)} \\
z_3^{(L)} &= w_{31}^{(L)} a_1^{(L-1)} + w_{32}^{(L)} a_2^{(L-1)} + w_{33}^{(L)} a_3^{(L-1)} + w_{34}^{(L)} a_4^{(L-1)} + w_{35}^{(L)} a_5^{(L-1)} + b_3^{(L)} \\
&= \sum_k w_{3k}^{(L)} a_k^{(L-1)} + b_3^{(L)}
\end{aligned}$$

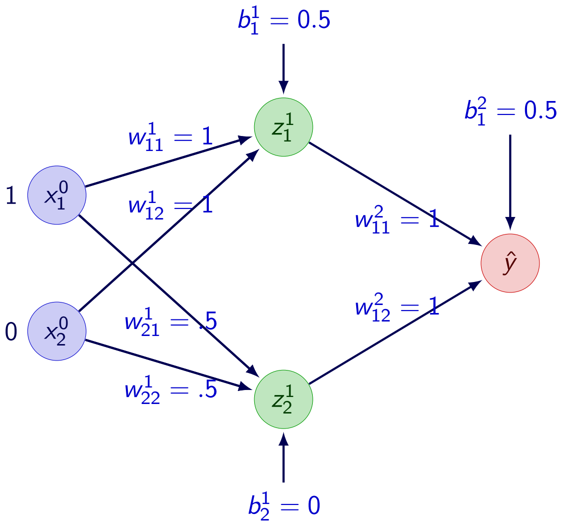
Forward Passing By Hand

Forward Passing By Hand

- Data point: $(x_1, x_2) = (1, 0)$
- Two layers: One hidden and one output layer
- Hidden layer has two neurons
- Output layer has one neuron
- Target is $y = 1$

We “randomly” initialize the weights

Our Network



$b_1^1 = 0.5$
$b_1^2 = 0.5$
$w_{11}^1 = 1$
z_1^1
1
x_1^0
$w_{12}^1 = 1$
$w_{11}^2 = 1$
$\hat{y}$
$w_{12}^2 = 1$
0
x_2^0
$w_{21}^1 = .5$
$w_{22}^1 = .5$
z_2^1
$b_2^1 = 0$

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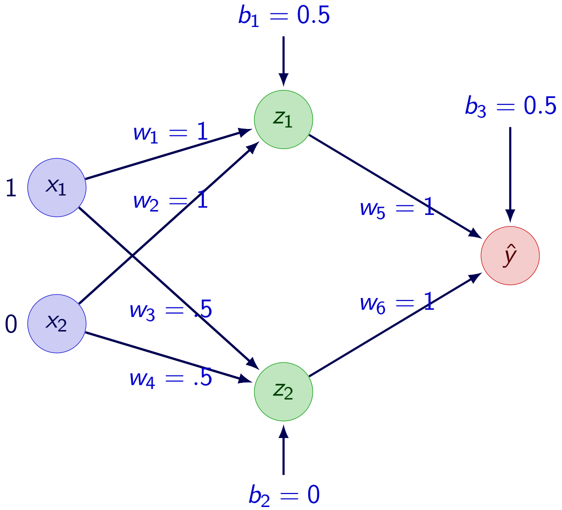

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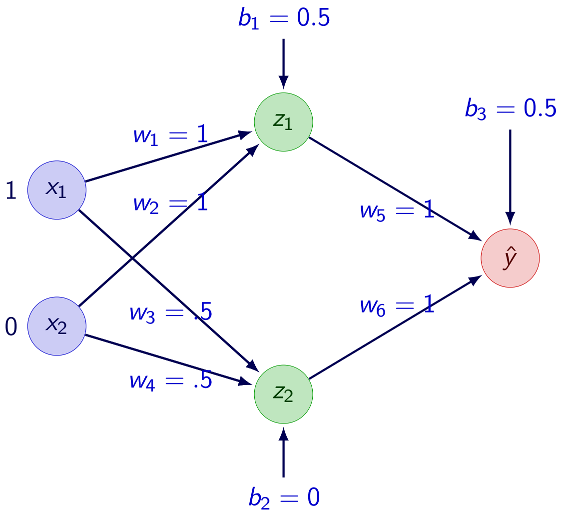

Complete the forward pass: What's $\hat{y}$?

Forward Calculations

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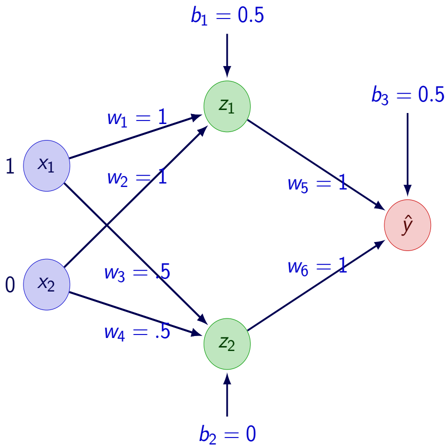

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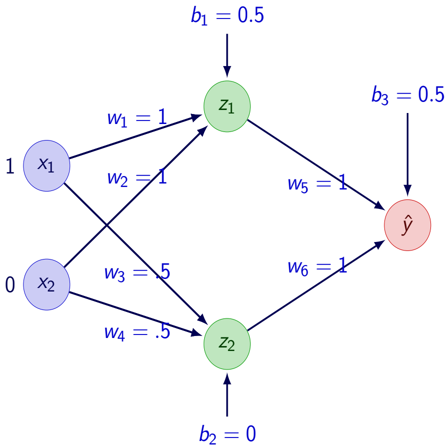

$$
\begin{aligned}
z_1 &= w_1 x_1 + w_2 x_2 + b_1 \\
&= 1 \cdot 1 + 1 \cdot 0 + 0.5 \\
&= 1 + 0 + 0.5 \\
&= 1.5
\end{aligned}
$$

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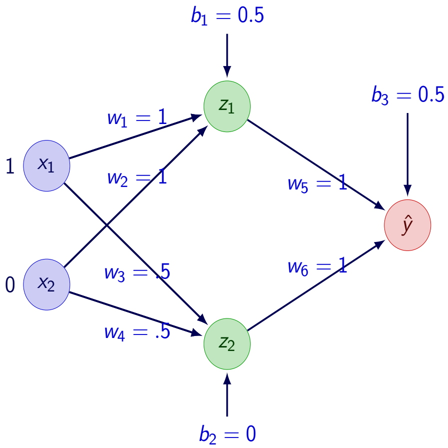

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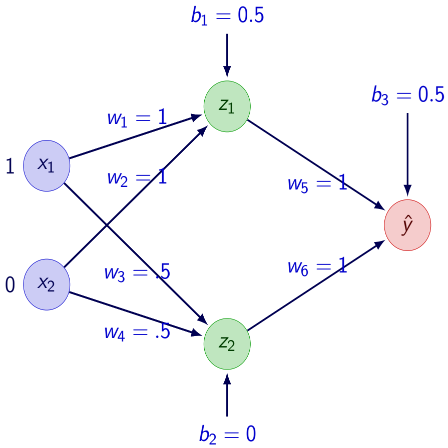
z_2 &= w_3 x_1 + w_4 x_2 + b_2 \\
&= 0.5 \cdot 1 + 0.5 \cdot 0 + 0 \\
&= 0.5 + 0 + 0 \\
&= 0.5
\end{aligned}
$$

Forward Calculations



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$$\begin{aligned} \hat{y} &= w_5 z_1 + w_6 z_2 + b_3 \\ &= 1 \cdot 1.5 + 1 \cdot 0.5 + 0.5 \\ &= 1.5 + 0.5 + 0.5 \end{aligned}$$

Cost Functions

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$$C = \frac{1}{2n} \sum_{x} \|y(x) - \hat{y}(x)\|^2$$

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For a single example x, it becomes: $C_x = \frac{1}{2}\|y - \hat{y}\|^2$.

Assume the target is $y = 2$. Compute the cost for our output $\hat{y} = 2.5$ (you can ignore the $\frac{1}{2}$)

Gradient Descent

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Because it then means that we can map x to y

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- Randomly initialize the weights

Gradient Descent

The objective of our NN is to correctly learn the function $y = f(x \mid w)$. Why?
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In practice:

- Stochastic Gradient Descent: **one data point**
- Mini-batch Gradient Descent: **one small batch**

Gradient Descent Illustration

Stochastic Gradient Descent: **one data point**

Gradient Descent Illustration

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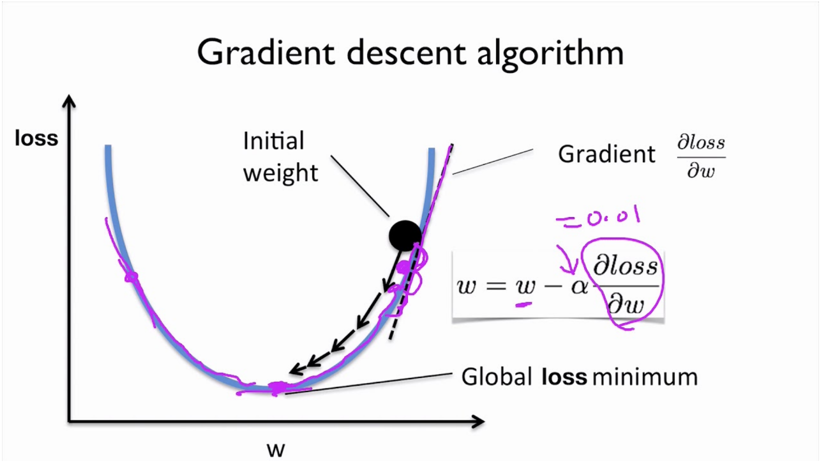

source: https://github.com/dshahid380/Gradient-descent-Algorithm

Backpropagation

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In a nutshell, the gradient encodes information about how we should adjust our weights to improve our output

To compute the gradient, we use the famous backpropagation algorithm

- Basic idea: Understand how changing the weights and biases changes the C
- Computes this by letting the cost from the forward pass C flow backward in the network to compute the gradient

Derivatives

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- Calculus is the mathematical study of continuous change
- Derivatives quantify the sensitivity of change of a function's output with respect to the input
  - $\rightarrow$ we find this by differentiation which we know, but (can't remember) from high school
- It's typically written as $f(x) = f'(x)$ or $\frac{d}{dx}$

Differentation Exercise

Example 1: $f(x) = x^2$

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Example 3: $x^2 + x^3$

Differentation Exercise

Example 1: $f(x) = x^2$

Example 2: $f(x) = 1/x$

Example 3: $x^2 + x^3$

Hints:

- the power rule: $x^n = nx^{n-1}$
- the sum rule: $f + g = f' + g'$

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$$\begin{aligned}\frac{d}{dx}x^2 + x^3 &= \frac{d}{dx}x^2 + \frac{d}{dx}x^3\\ &= 2x^{2-1} + 3x^{3-1}\\ &= 2x + 3x^2\end{aligned}$$

The Chain Rule

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The chain rule of calculus is used to find the derivative of a function that itself is a function

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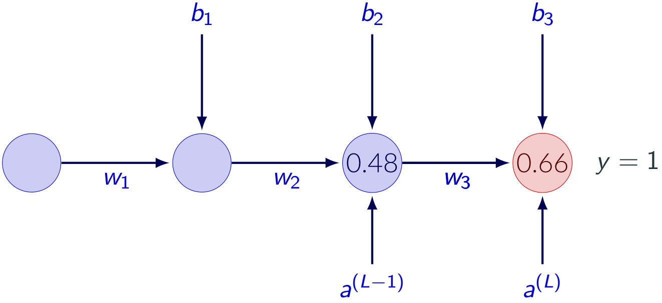
$g'(x) = 5$

We can then plugin and calculate the expression:

$$\begin{aligned} \frac{d}{dx}(5x-2)^3 &= (3g(x)^2)(5) \\ &= 15(5x-2)^2 \end{aligned}$$

Backpropagation In Action

We imagine we have a simple NN with three layers each with a single neuron:



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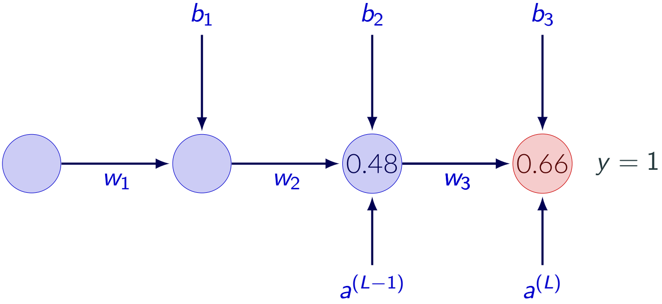

$$\begin{aligned} C &= (a^{(L)} - y)^2 \\ &= (0.66 - 1)^2 \end{aligned}$$

$$\begin{aligned} z^{(L)} &= w^L \cdot a^{(L-1)} + b^L \\ a^{(L)} &= g(z^{(L)}) \end{aligned}$$

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$$\frac{\partial C}{\partial w^L} = \frac{\partial z^L}{\partial w^L} \frac{\partial a^L}{\partial z^L} \frac{\partial C}{\partial a^L}$$

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$$\begin{aligned}\frac{\partial C}{\partial a^L} &= \frac{\partial (a^{(L)} - y)^2}{\partial a^L} \\ &= 2(a^{(L)} - y)\end{aligned}$$

$$\frac{\partial a^L}{\partial z^L} = g'\left(z^{(L)}\right)$$

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From all this, we can go ahead and compute the gradient, which is how the NN learns (recall: gradient descent)

The Gradient

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The gradient is a fancy way of saying: *how much should we change our weights to minimize the cost?*

$$-\nabla C = \begin{bmatrix} \frac{\partial C}{\partial w^1} \\ \frac{\partial C}{\partial b^1} \\ \frac{\partial C}{\partial w^2} \\ \frac{\partial C}{\partial b^2} \\ \vdots \\ \frac{\partial C}{\partial w^L} \\ \frac{\partial C}{\partial b^L} \end{bmatrix} = \begin{bmatrix} +0.31 \\ +0.03 \\ -1.25 \\ -0.10 \\ \vdots \\ +0.85 \\ +0.10 \end{bmatrix}$$

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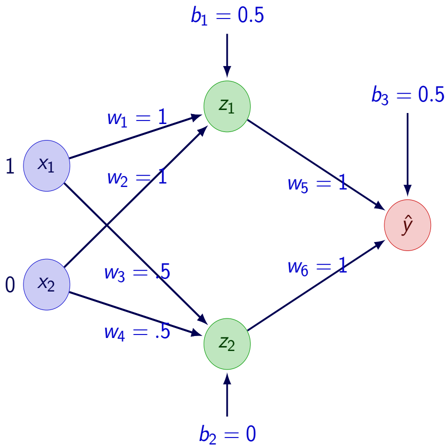
Backward Calculation



$$
\begin{aligned}
z_1 &= w_1 x_1 + w_2 x_2 + b_1 \\
&= 1 \cdot 1 + 1 \cdot 0 + 0.5 \\
&= 1 + 0 + 0.5 \\
&= 1.5
\end{aligned}
$$

$$
\begin{aligned}
z_2 &= w_3 x_1 + w_4 x_2 + b_2 \\
&= 0.5 \cdot 1 + 0.5 \cdot 0 + 0 \\
&= 0.5 + 0 + 0 \\
&= 0.5
\end{aligned}
$$

$$
\begin{aligned}
\hat{y} &= w_5 z_1 + w_6 z_2 + b_3 \\
&= 1 \cdot 1.5 + 1 \cdot 0.5 + 0.5 \\
&= 1.5 + 0.5 + 0.5 \\
&= 2.5
\end{aligned}
$$

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Lab

Dense vs. Convolutional Layers

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A typical convolutional layer has three steps:

1. Convolution
2. Activation
3. Pooling

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- Input image M with dimension $N \times N$

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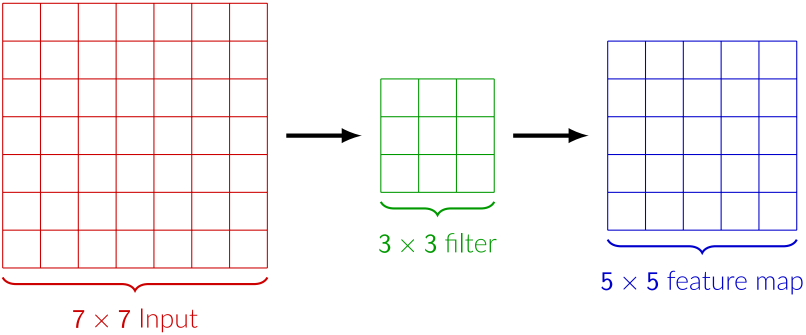

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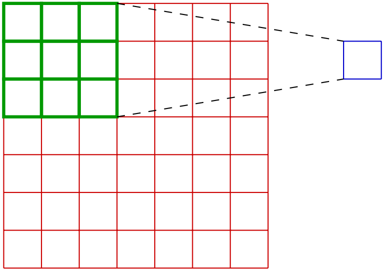
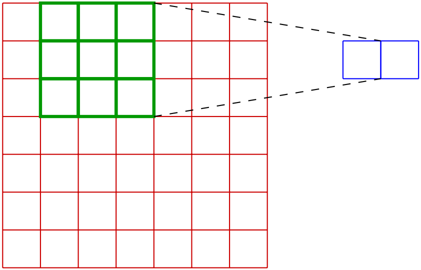
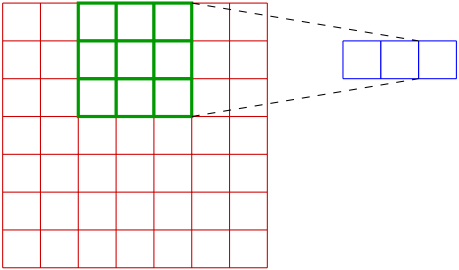
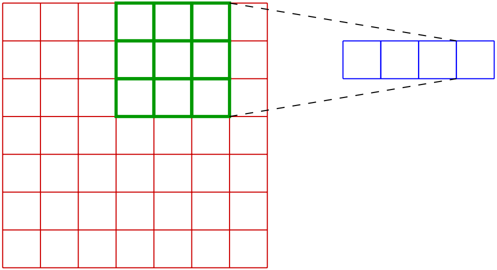
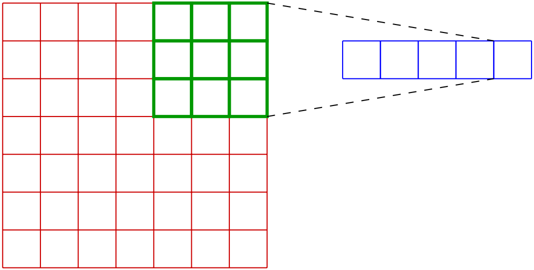
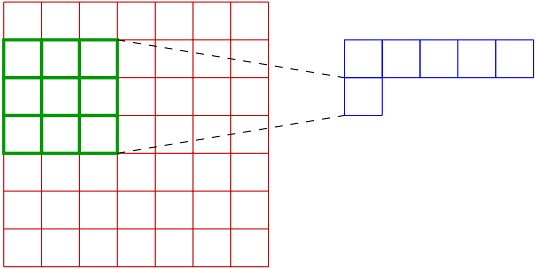


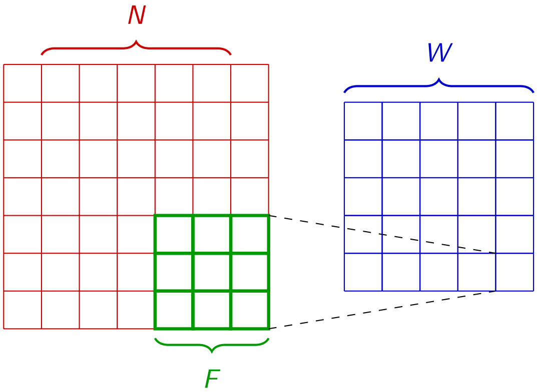


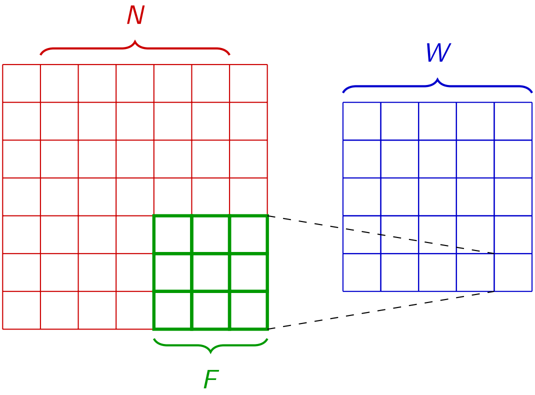









N
W
F



The width of the feature map is represented by the formula:

$$W = \frac{N + 2P - F}{S} + 1$$

where P is the width of the padding and S is the stride

Convolution Exercise

Convolution Exercise

You have:

- $128 \times 128 \times 3$ input
- One 5×5 filter
- Padding: 2
- Stride: 1

$W = \frac{N+2P-F}{S} + 1$

Questions:

1. What's the output dimension of the feature map?
2. What's the number of parameters?
3. What if $F = N + 2P$?

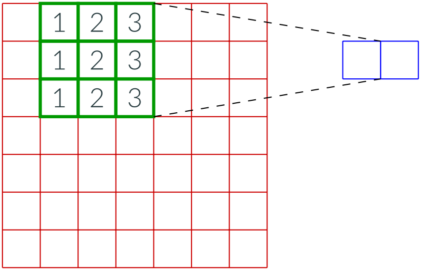
Calculation

Calculation

Filter:

0	0	1
0	1	0
1	0	0

Input matrix:



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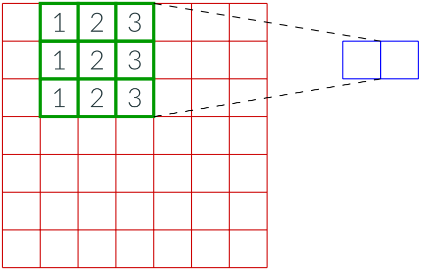

$$
= \begin{bmatrix} 1 \cdot 0 & 2 \cdot 0 & 3 \cdot 1 \\ 1 \cdot 0 & 2 \cdot 1 & 3 \cdot 0 \\ 1 \cdot 1 & 2 \cdot 0 & 3 \cdot 0 \end{bmatrix}
$$

$$
= \begin{bmatrix} 0 & 0 & 3 \\ 0 & 2 & 0 \\ 1 & 0 & 0 \end{bmatrix}
$$

$$
= 6
$$

Filters/Kernels

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1. Compress the image
2. Learn features

Filters/Kernels

The filters are the core of the convolution ⇝ the weight matrices for CNNs

The purpose of filters is to simultaneously:

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⇝ Encoded by the feature map, which quantifies how much a spatial location resembles the filter (e.g. lines, corners, shapes)

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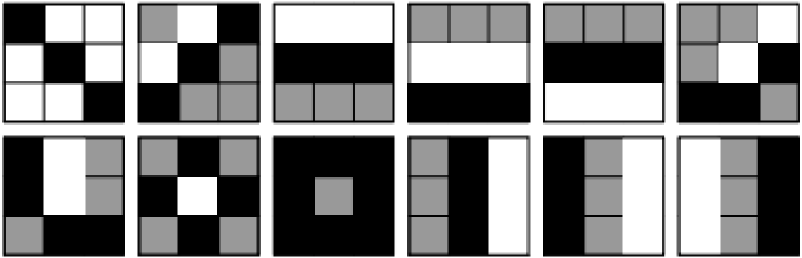
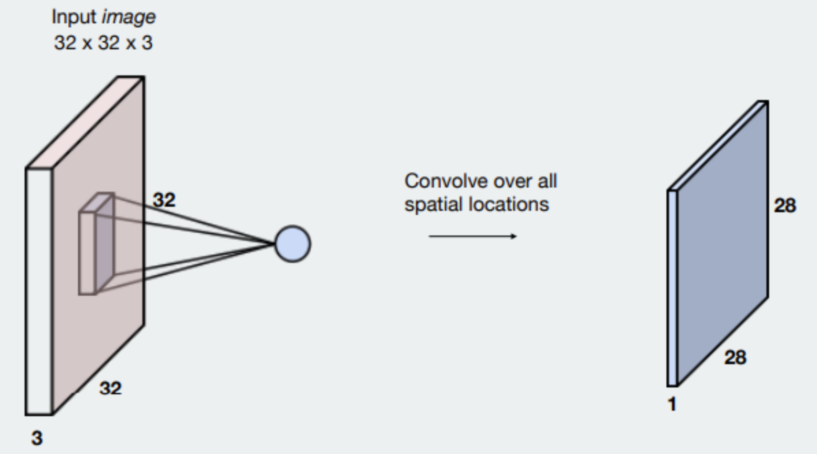
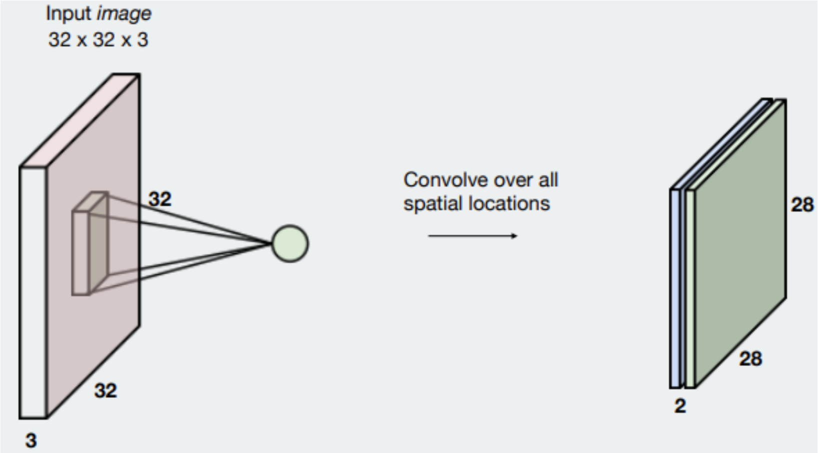
Example of 3×3 filters:



One Filter


Input *image*
32 x 32 x 3
32
32
3
Convolve over all
spatial locations
28
28
1

Two Filters



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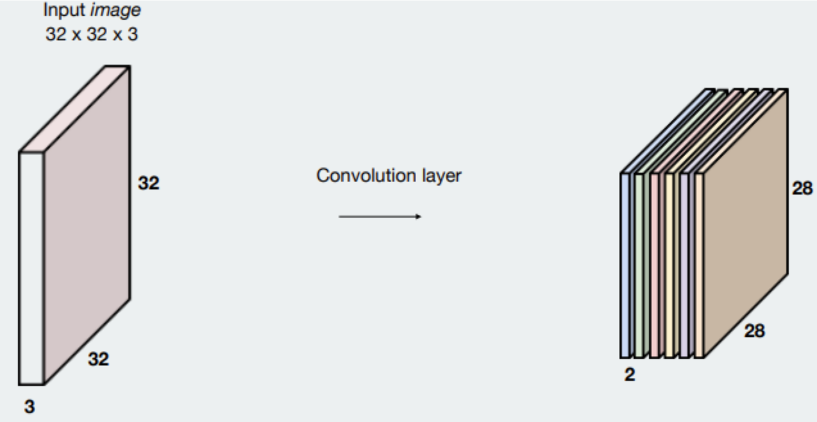
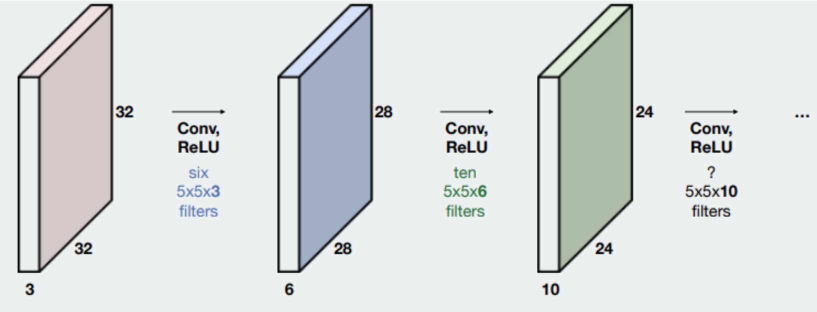
Multiple Filters



Stacking Convolutional Layers



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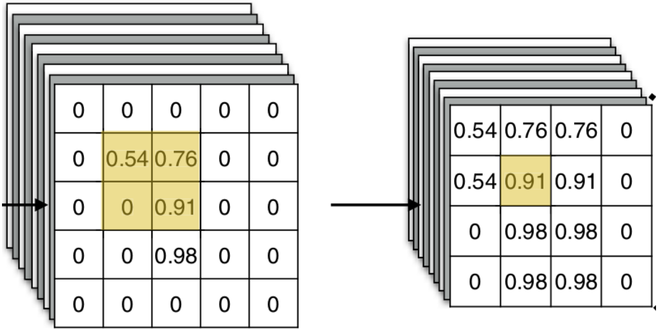

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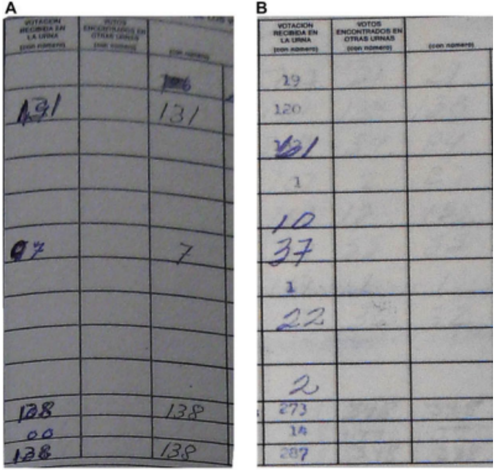
Example: Handwriting Recognition and Electoral Fraud (Cantú, 2019)



Training a Neural Network

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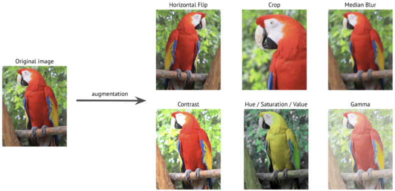

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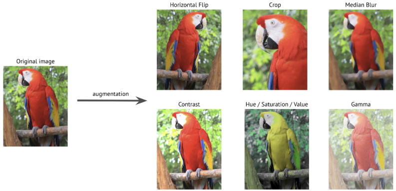
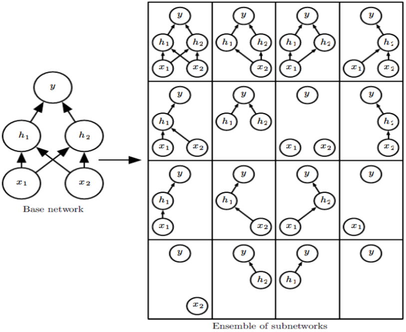


Dropout:



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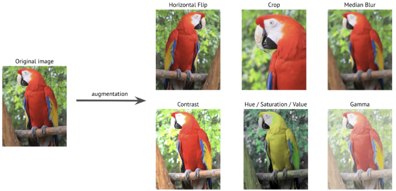

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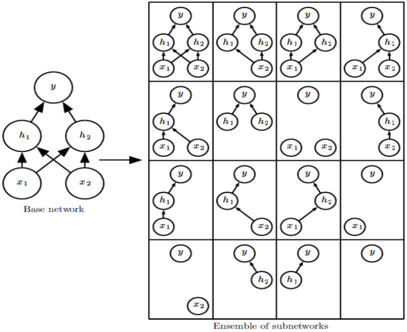
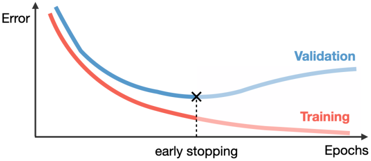


Early Stopping:

Stop training when performance on the validation dataset starts worsening



Transfer Learning

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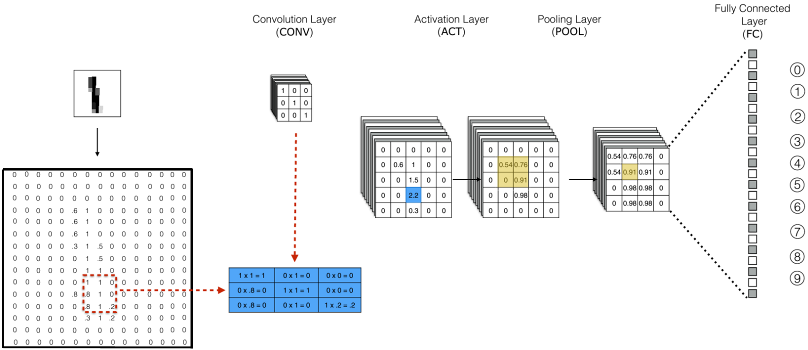

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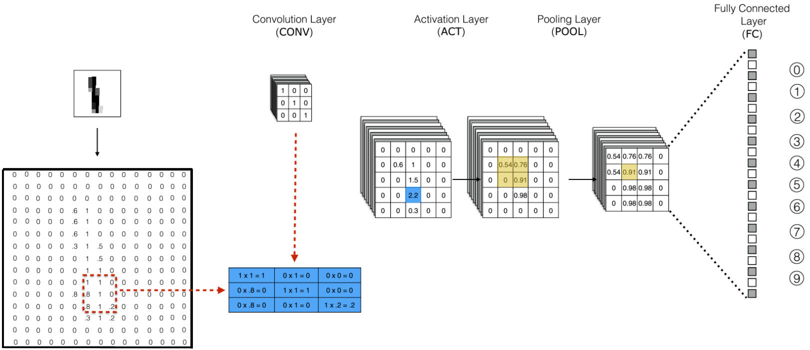

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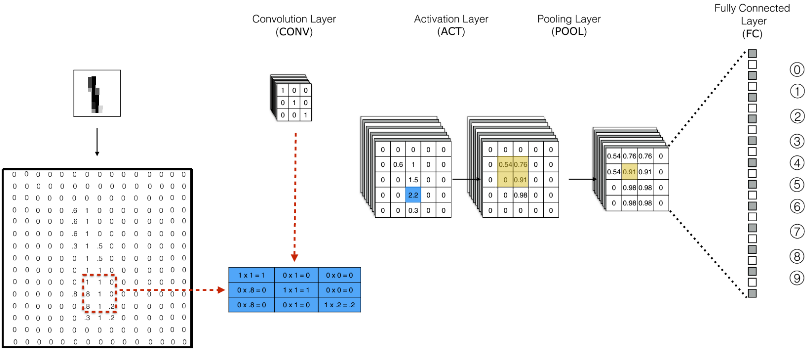

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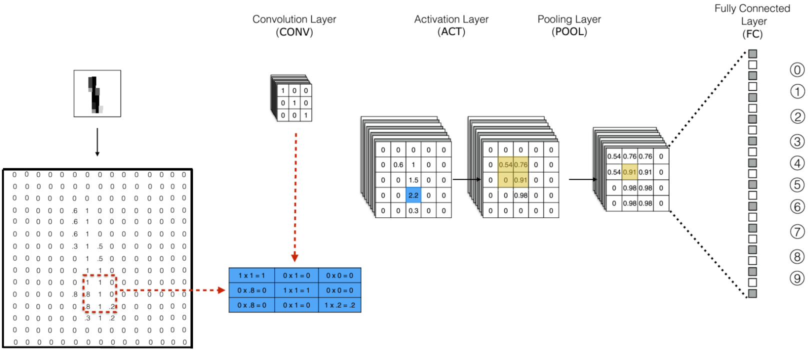

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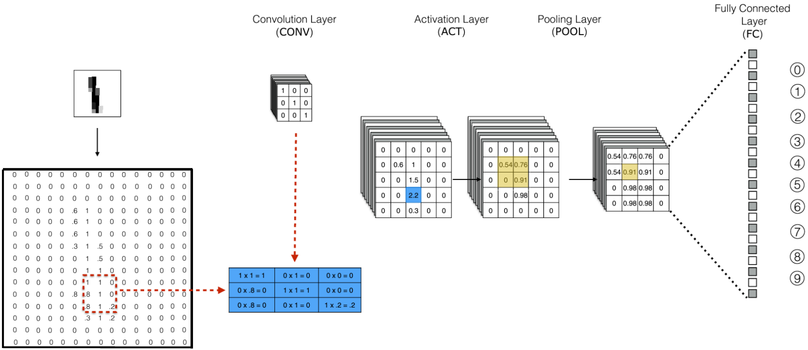

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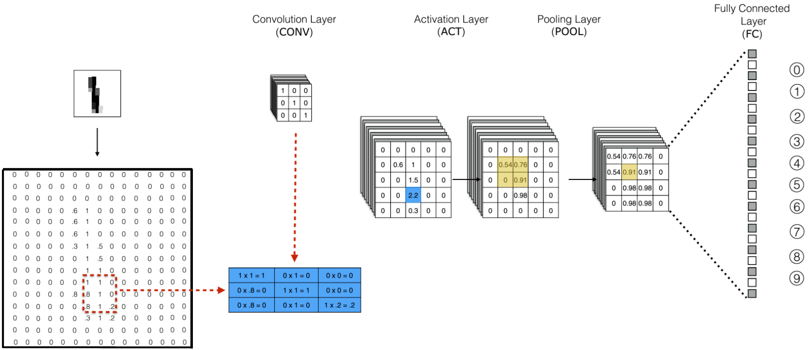

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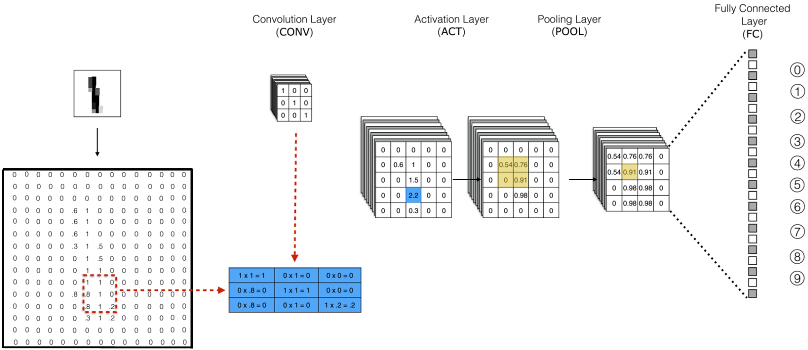

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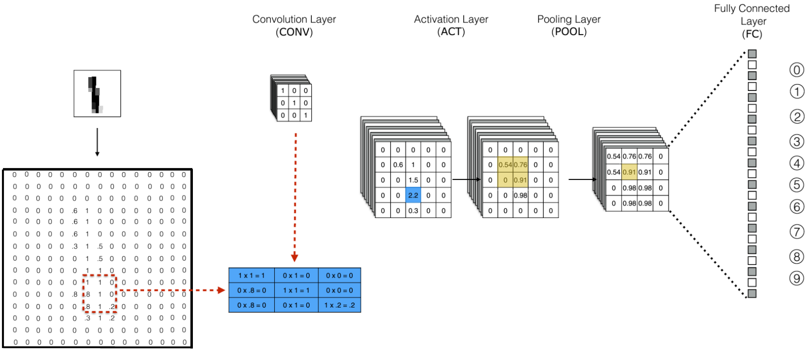

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See you next week!

Topic 4: Images

Computational Analysis of Text, Audio, and Images, Fall 2023

Aarhus University

References i

[1] F. Cantú, "The fingerprints of fraud: Evidence from mexico's 1988 presidential election," *American Political Science Review*, vol. 113, no. 3, pp. 710–726, 2019.