CNN and Pytorch

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Laboratoire Interdisciplinaire des Sciences du Numérique – LISN, CNRS

The lecture

A short introduction to CNN and Pytorch

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1. The Convolutional neural networks: A short presentation

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1. The Convolutional neural networks: A short presentation
2. Introduction to pytorch (using slides of Caio Corro)

Convolutional Neural Networks

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A neural network specialised using convolution functions as module

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- In image processing using 2D convolutions
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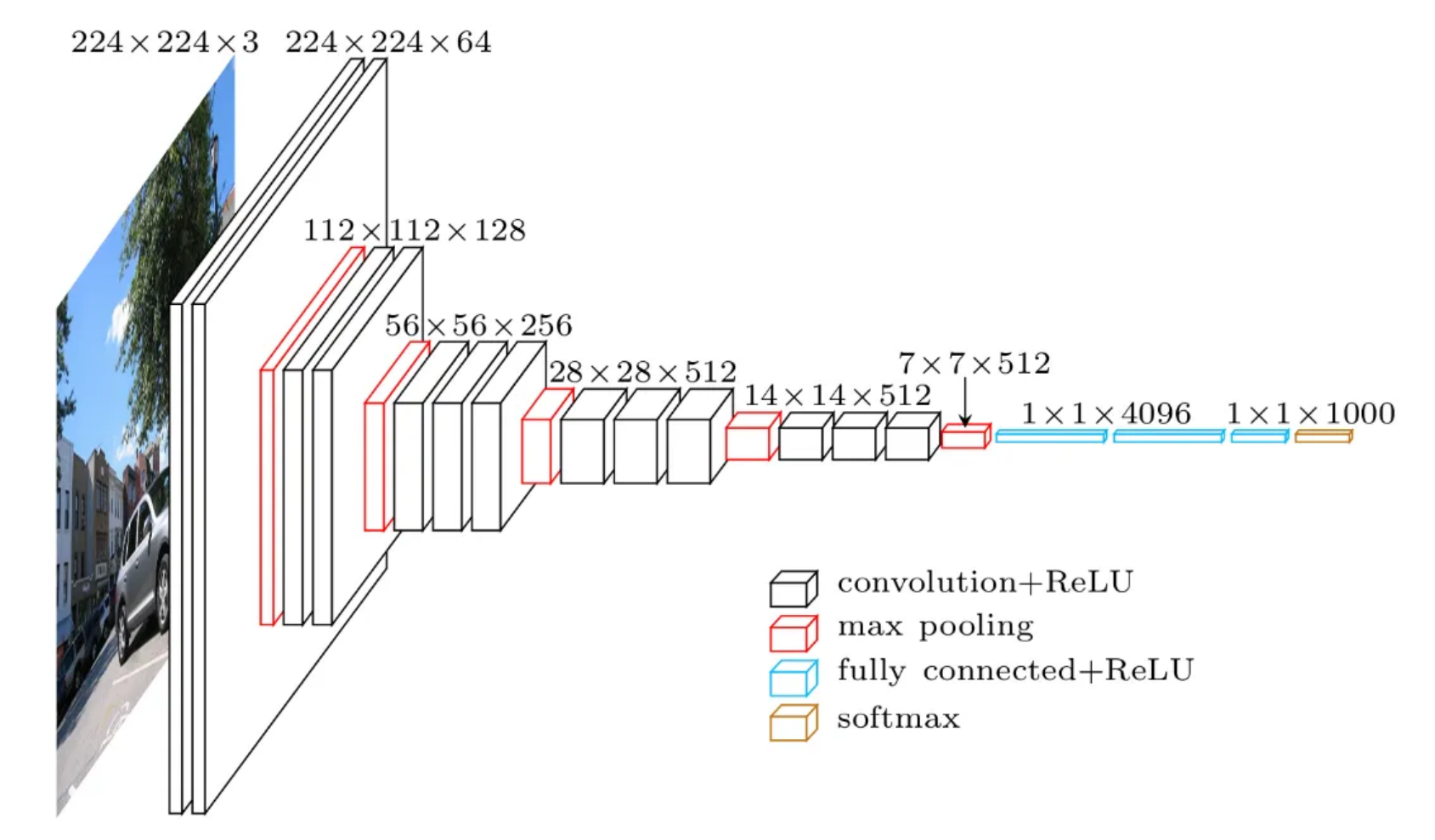
- In text processing such as classification (1D convolutions)

Convolutional Neural Networks: Image classification

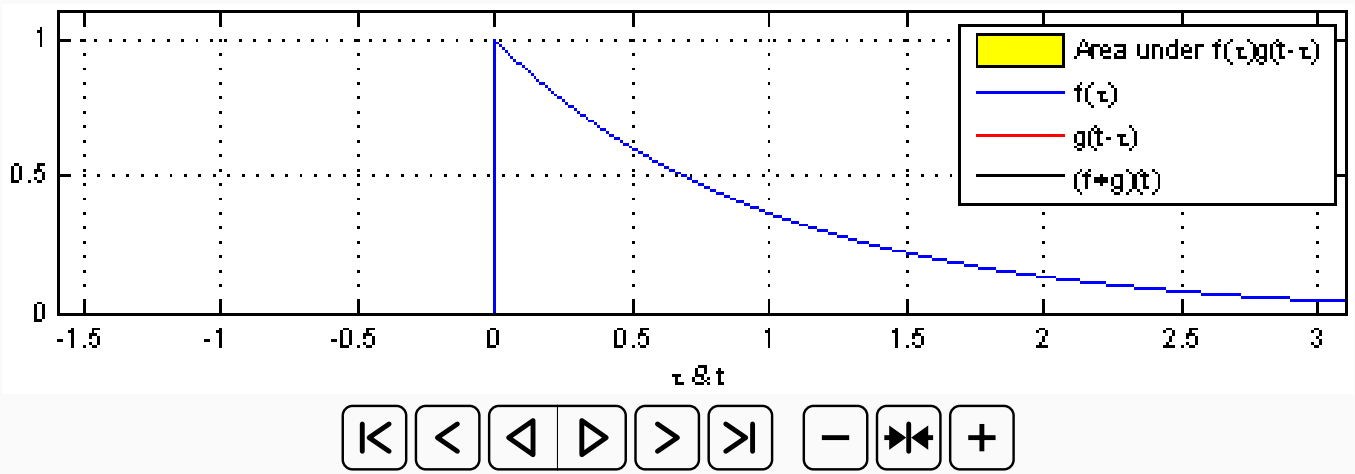


[0]VGG16 architecture for image classification image from https://miro.medium.com/v2/resize:fit:4800/format:webp/1*CrjJwSX9S7f759dK2EtGJQ.png

Convolution operation

Let f and g be two functions the convolution operation between f and g is generally written $f * g$ such that:

$$(f * g)(t) := \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau$$



Discrete Convolution operation

Working with computer data, we often consider discretized time steps. Thus, the time index t take integer values only.

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- The input function f is often a multidimensional array X
- The kernel function g is often a multidimensional array K

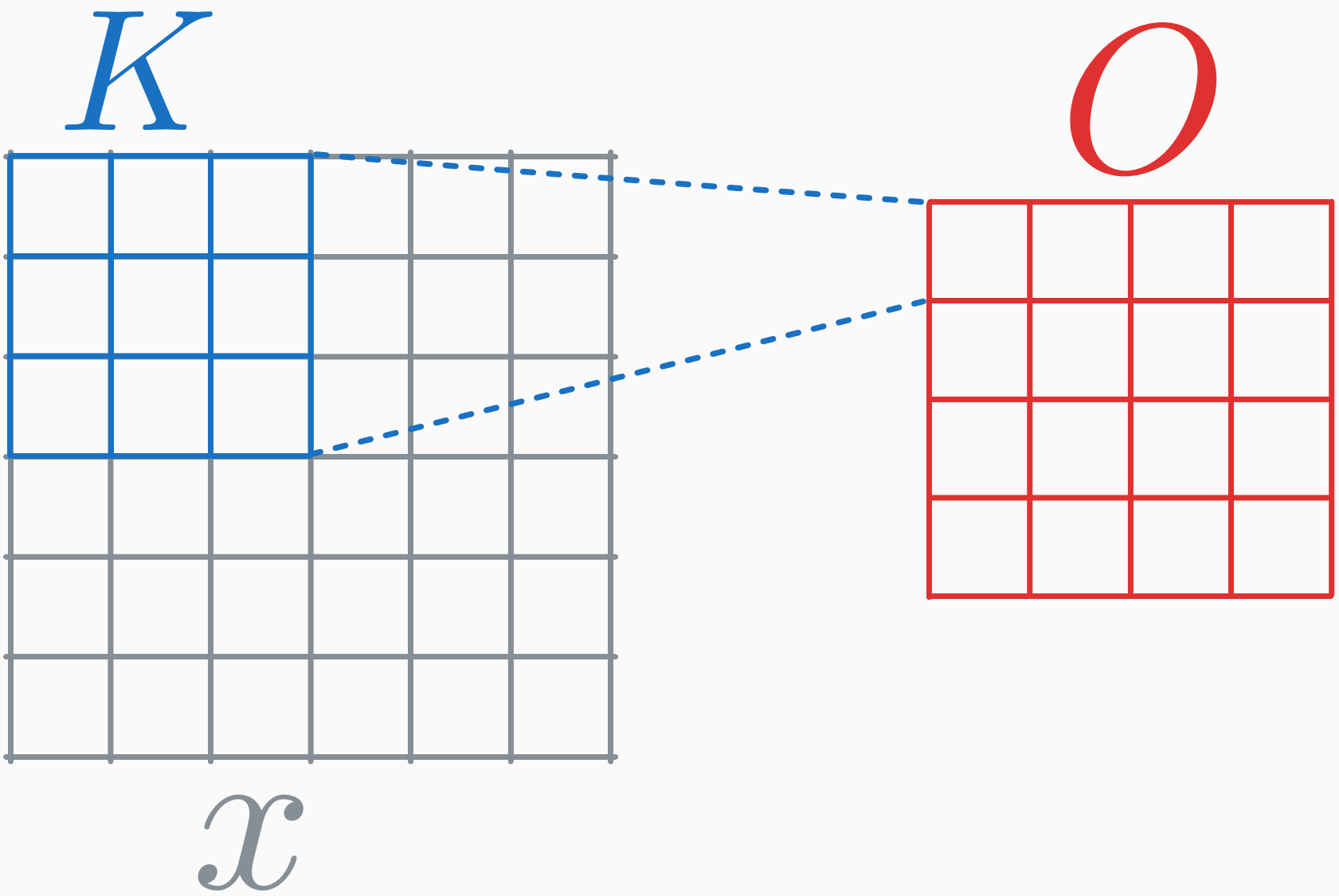
$\rightarrow$ Thus these functions are assumed as zero elsewere (defined only for the value stored)

Convolutional Neural Networks: 2D convolution

Let $x \in \mathbb{R}^{A,B}$ be a matrix (for instance an image) and $K \in \mathbb{R}^{N,M}$ an other matrix (the convolution kernel), we define the output of the convolution (in i and j) as:

$$O_{i,j} = (x * K)_{i,j} = \sum_{n=1}^{N} \sum_{m=1}^{M} x_{i+n,j+m} K_{n,m}$$

Convolutional Neural Networks: The convolution on matrix



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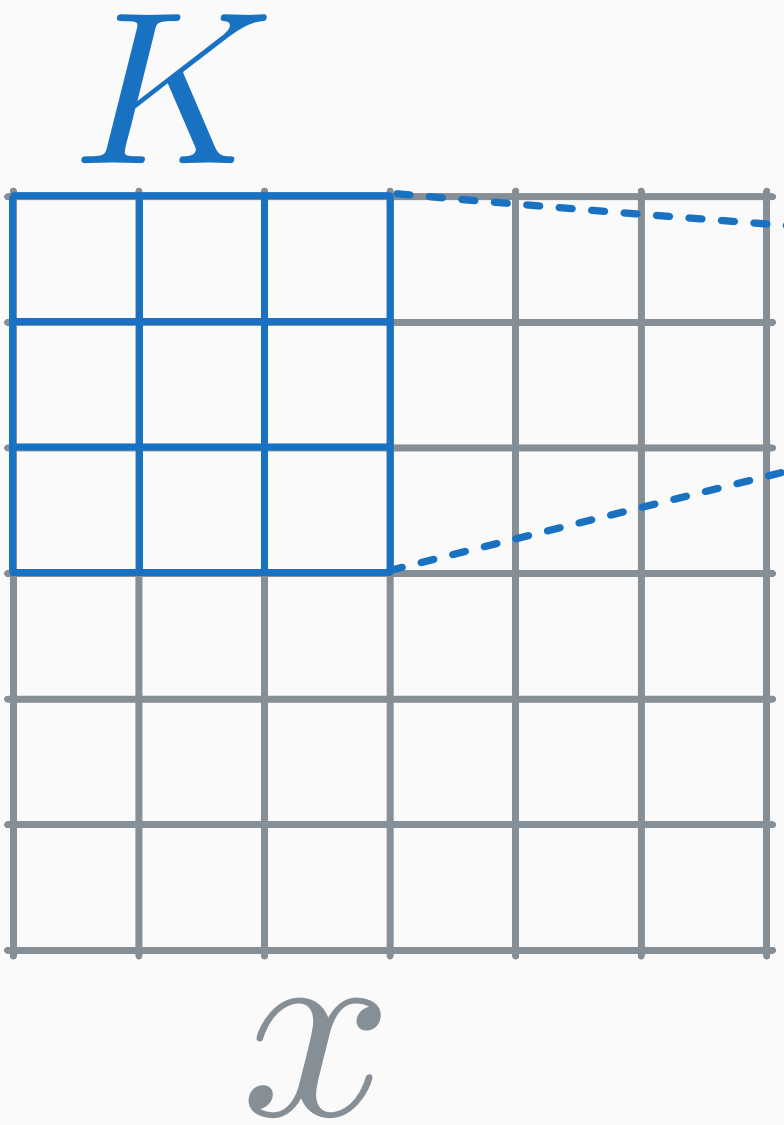

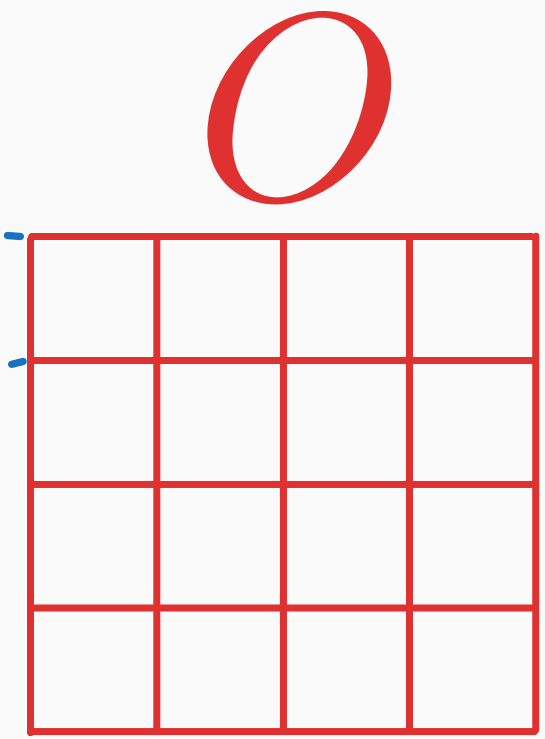

$$O_{i,j} = \sum_{n=1}^{W} \sum_{m=1}^{H} x_{i+n,j+m} K_{n,m}$$

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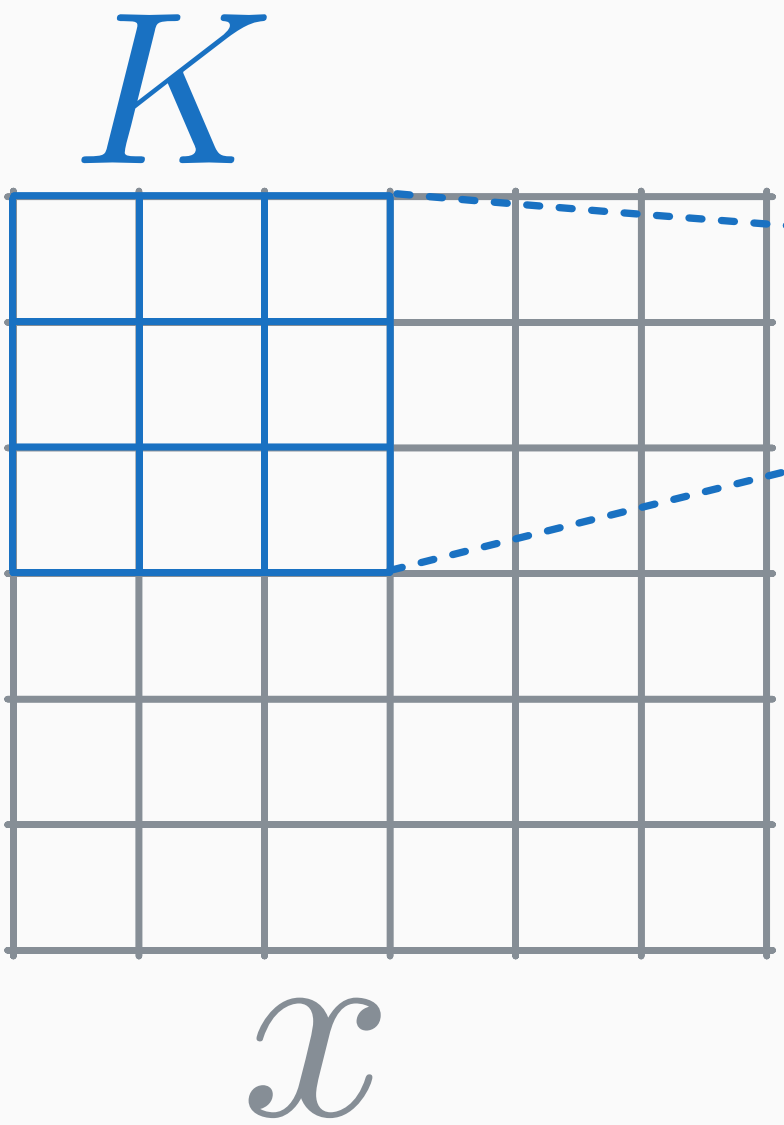

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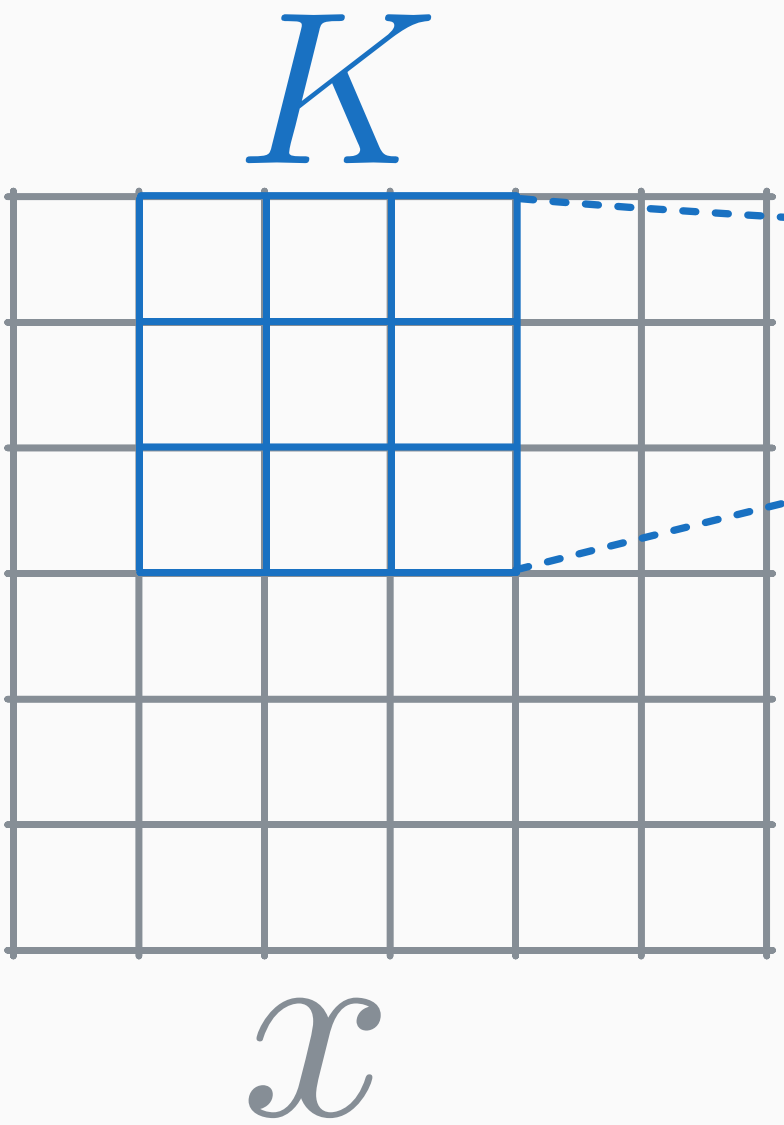

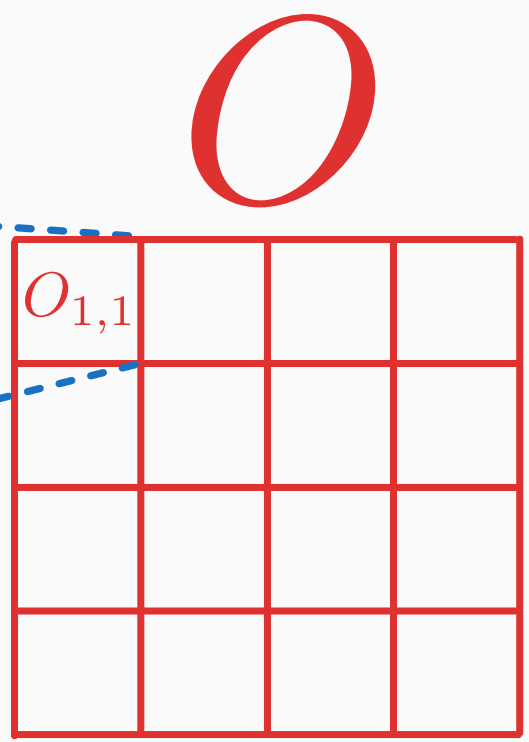

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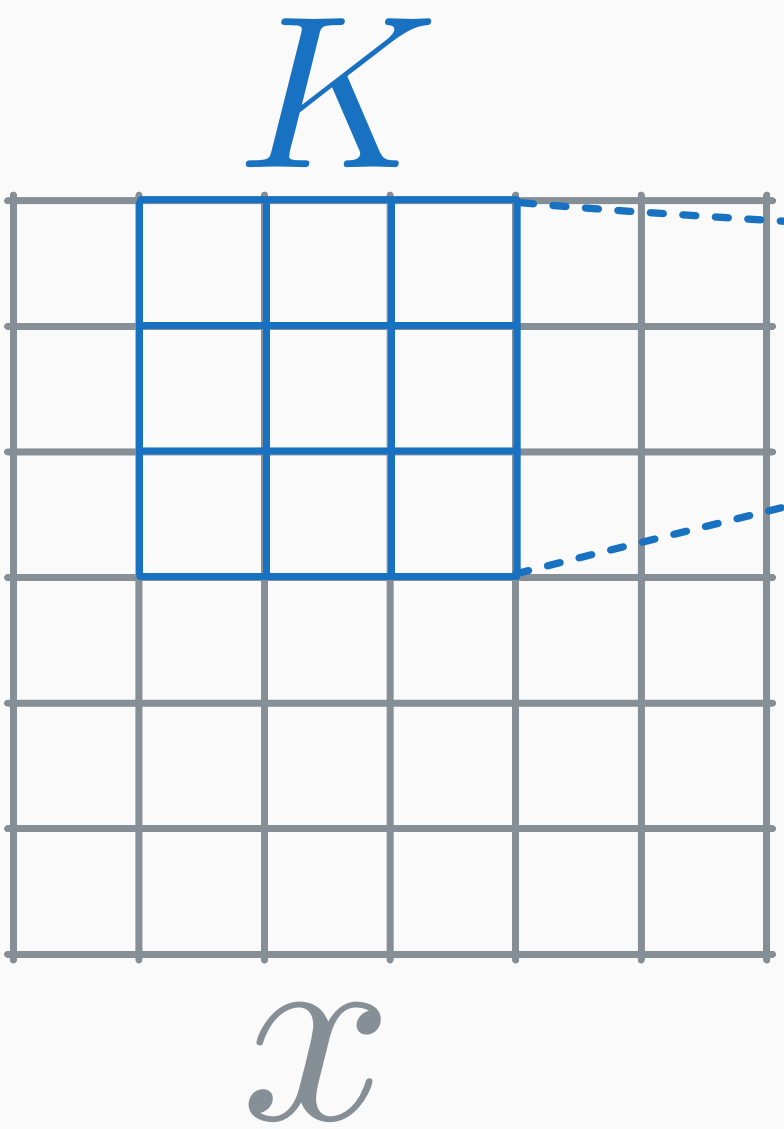

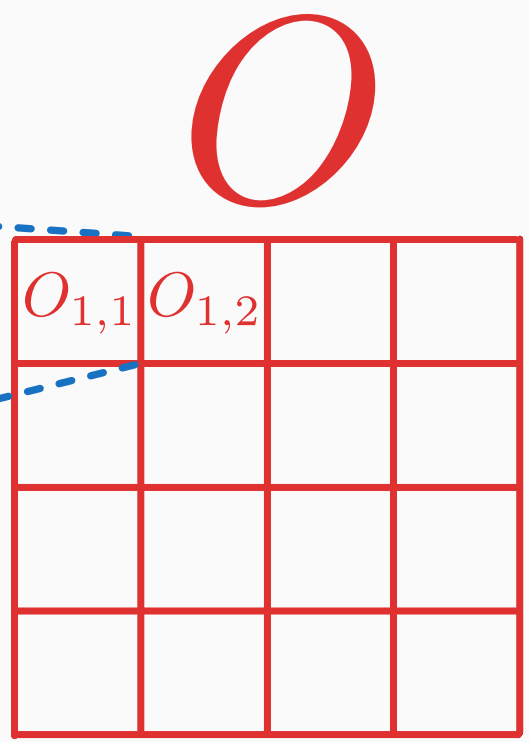

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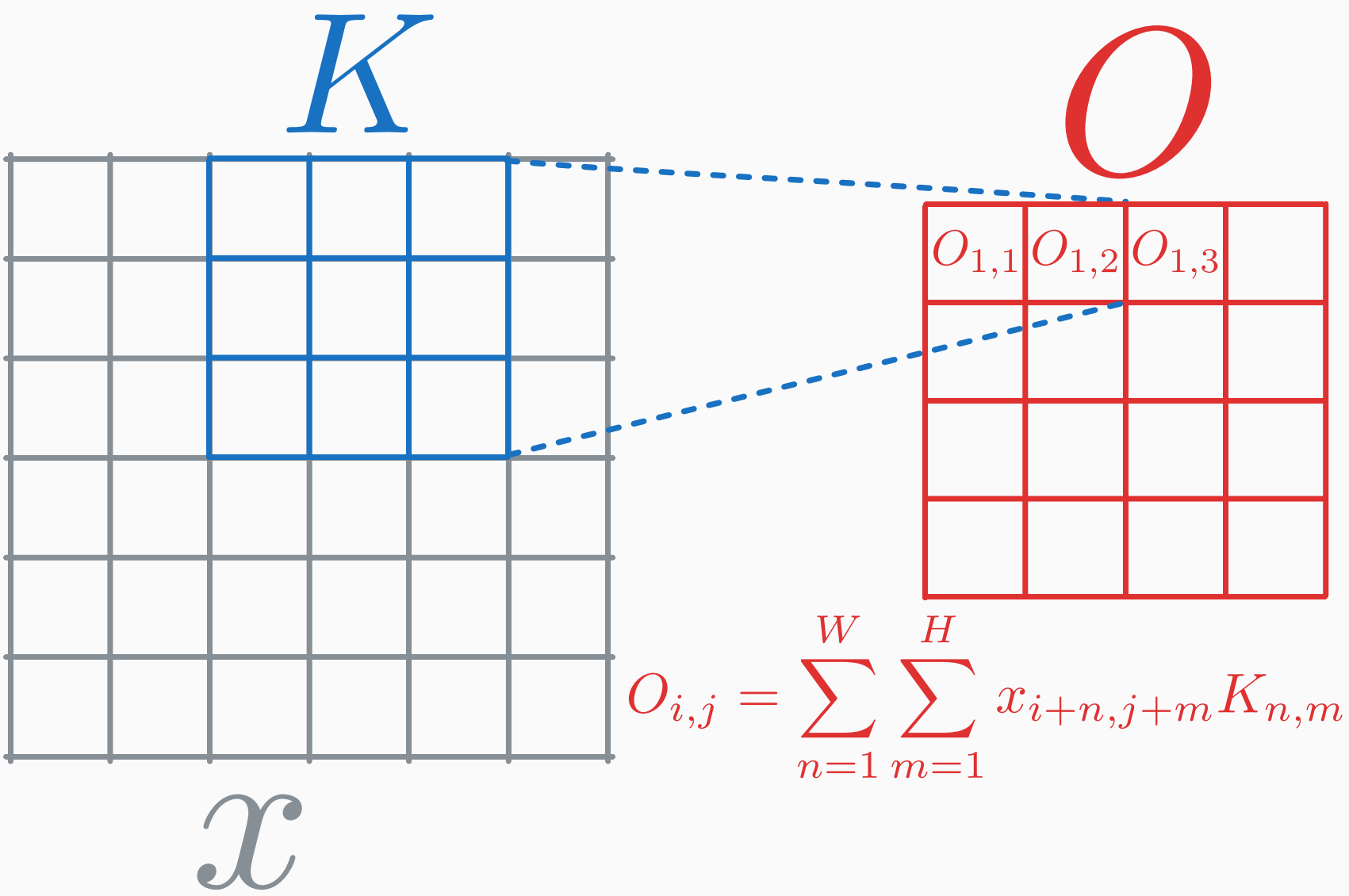

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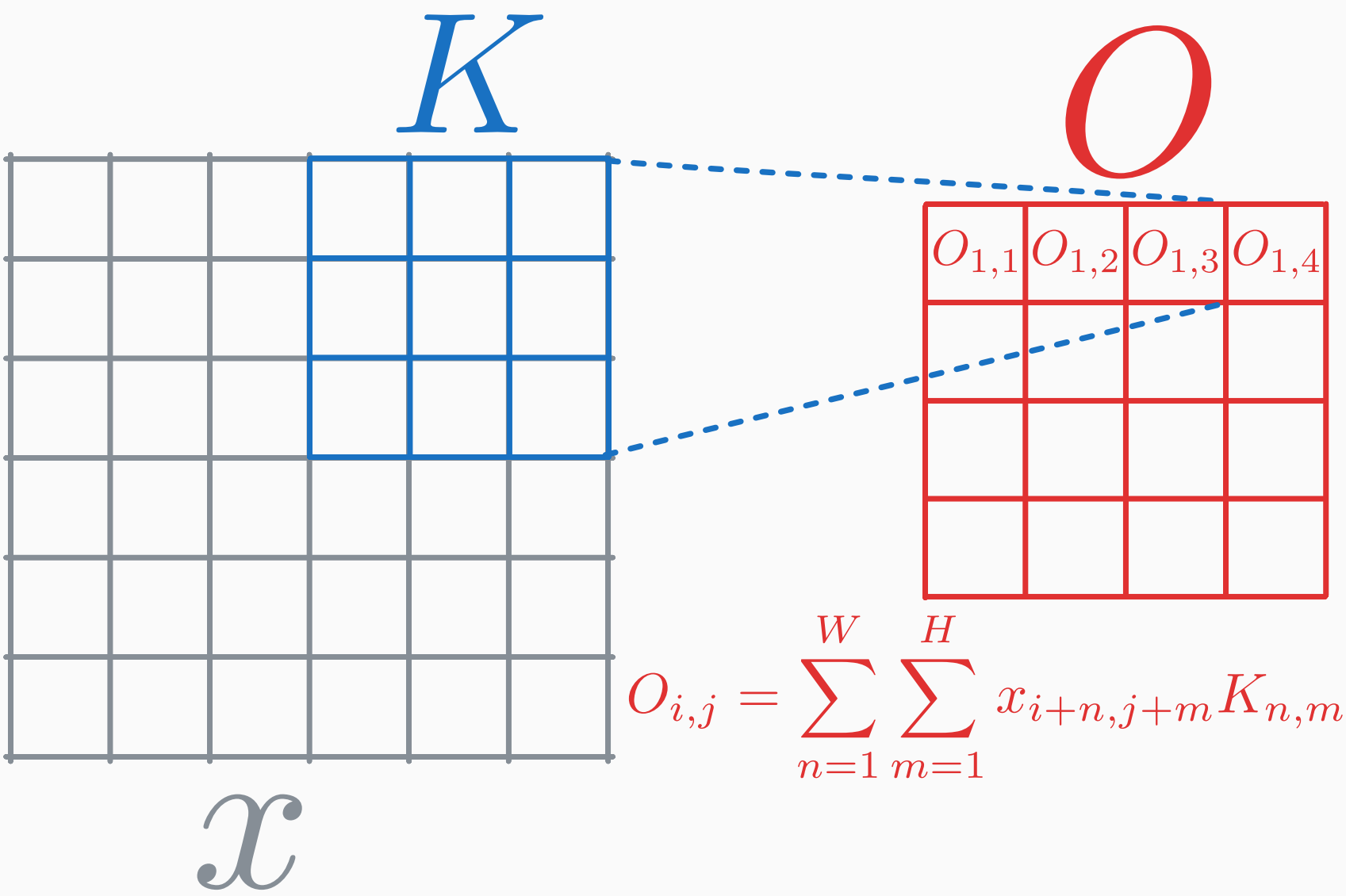

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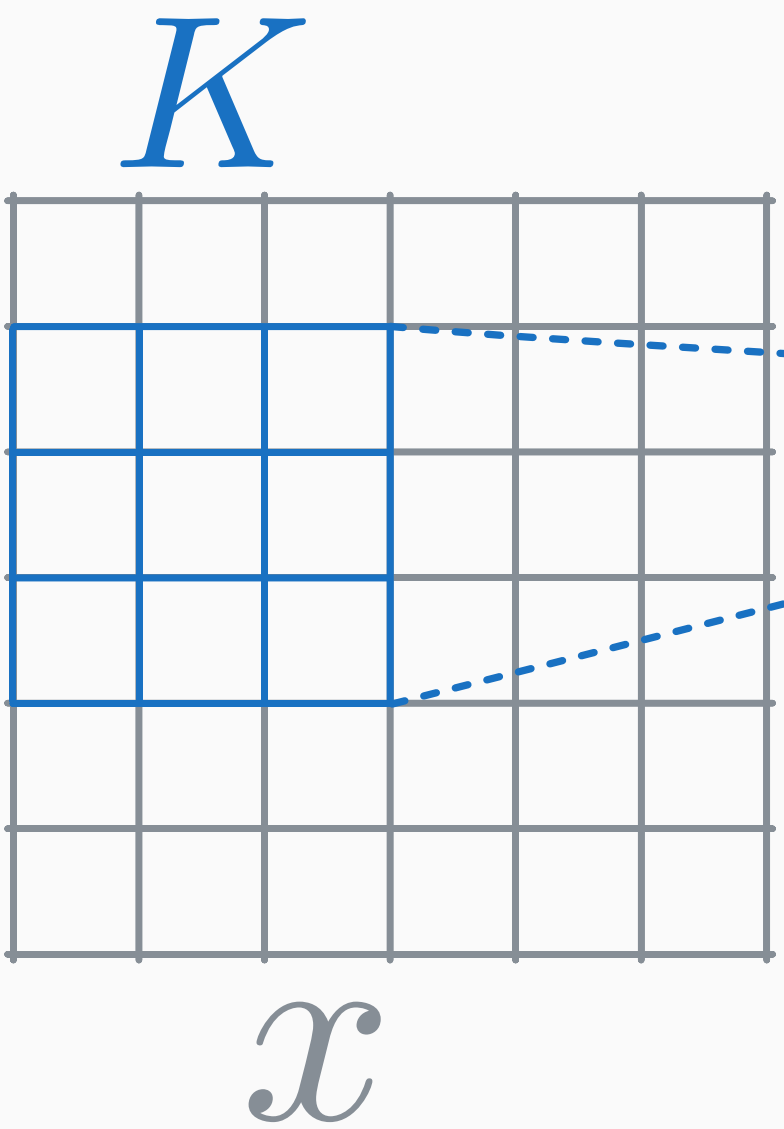

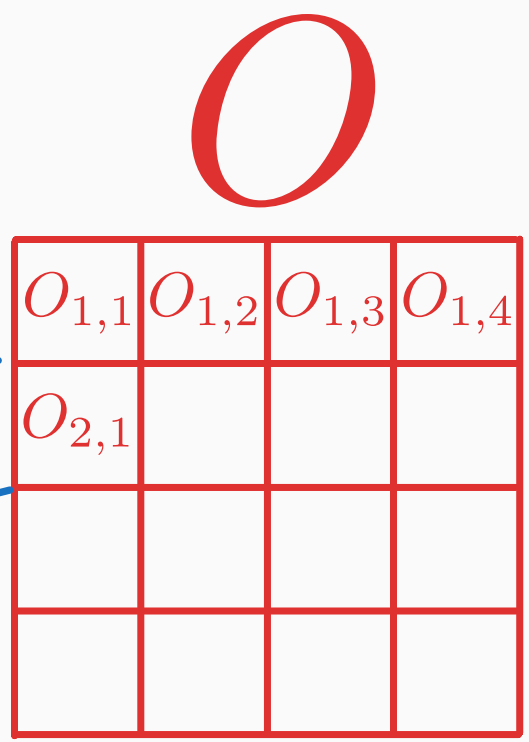

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Finding borders (sharpening kernel)

Let

$$K = \begin{pmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{pmatrix}$$

be the convolution kernel

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Convolution for different utilities

Bluring kernel

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$\rightarrow$ a new pixel is the average of all its neighbor pixel

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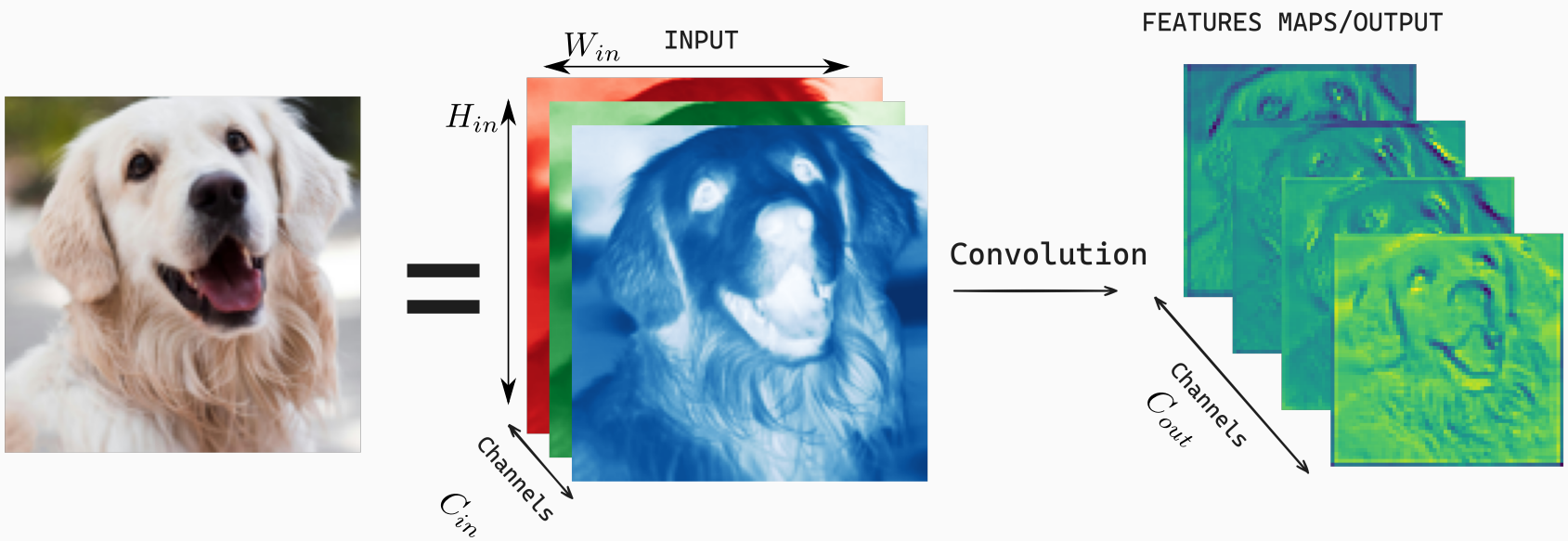
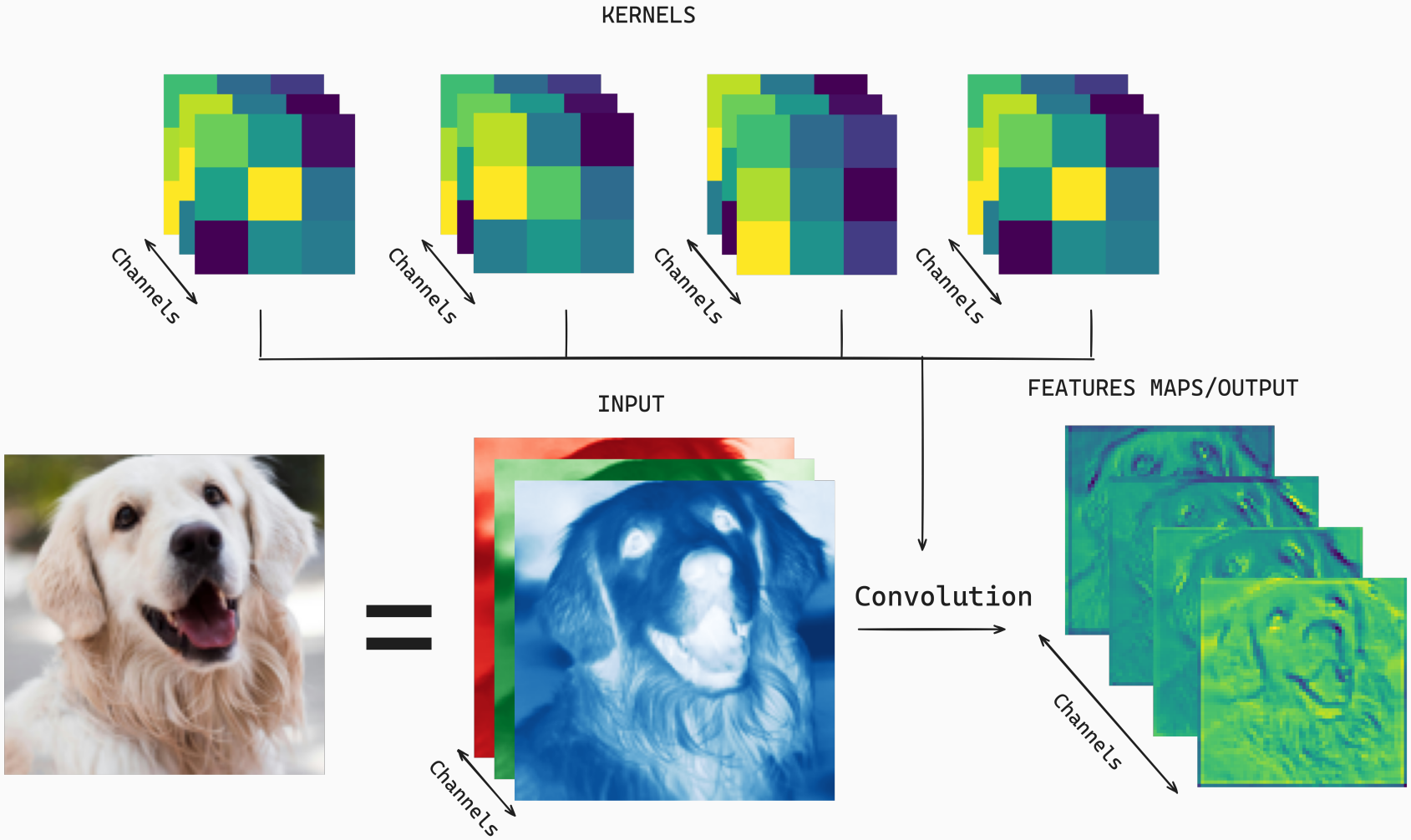


Convolutional Neural Networks



Convolutional Neural Networks: with stride

Stride in convolution

Move the window in each convolution steps of s pixels (an integer)

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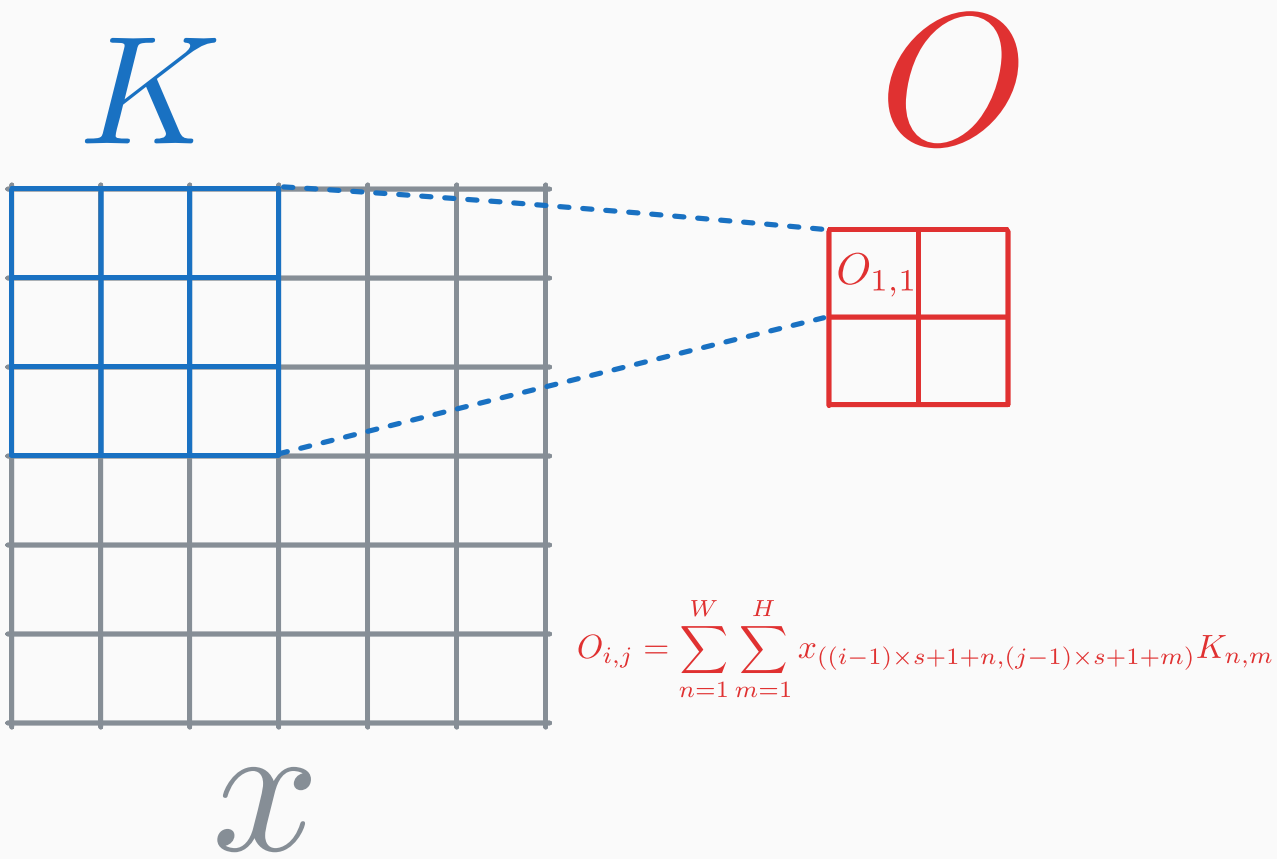

$$O_{i,j} = \sum_{n=1}^{W} \sum_{m=1}^{H} x_{((i-1)\times s+1+n,(j-1)\times s+1+m)} K_{n,m}$$

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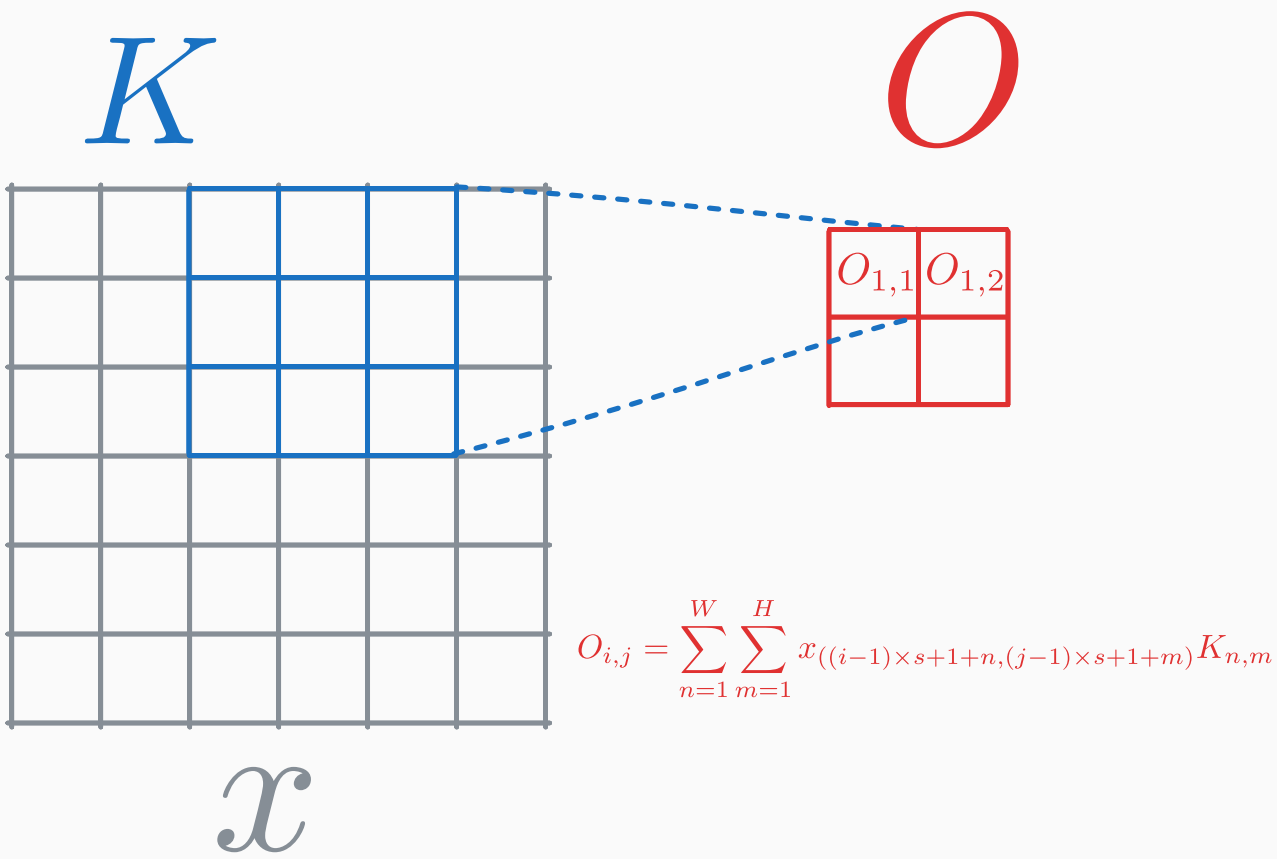

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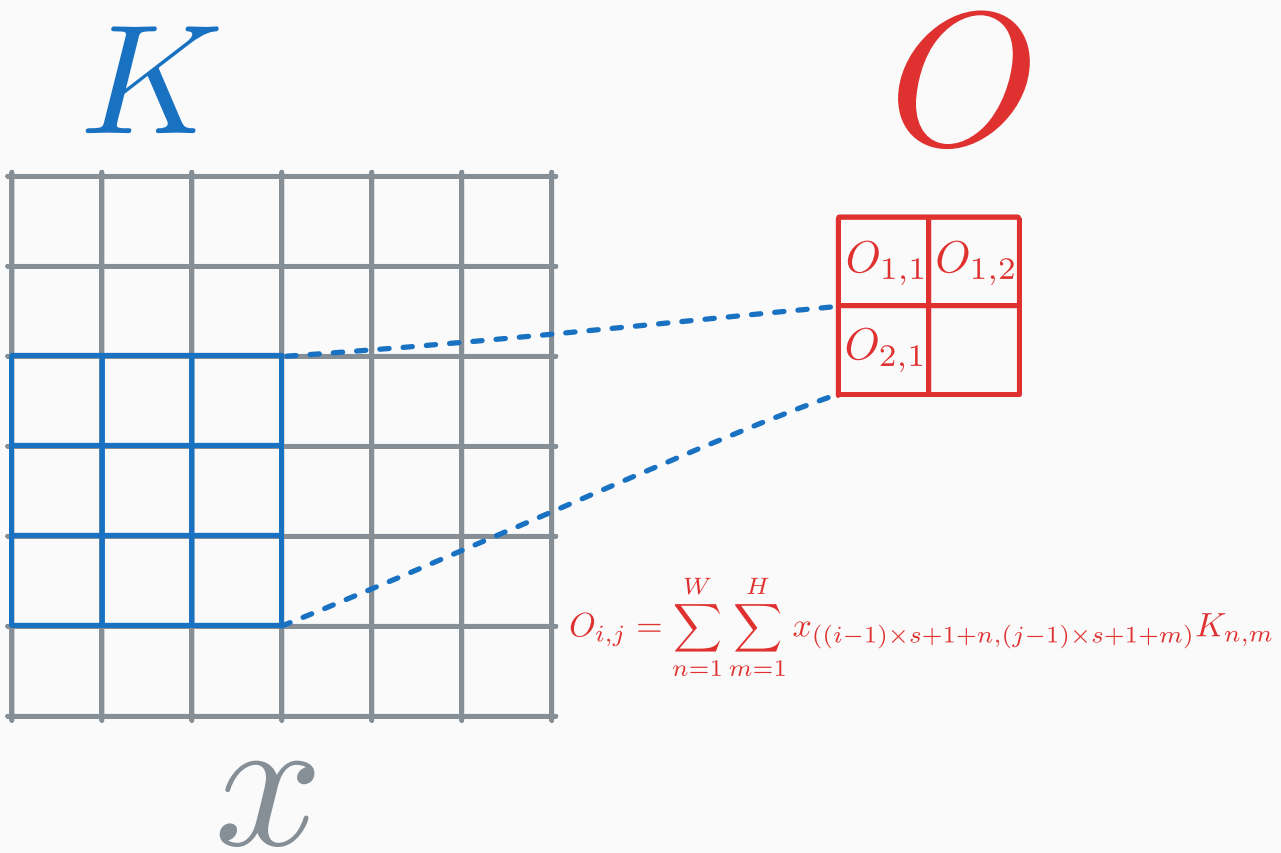


Padding in convolution

Padding

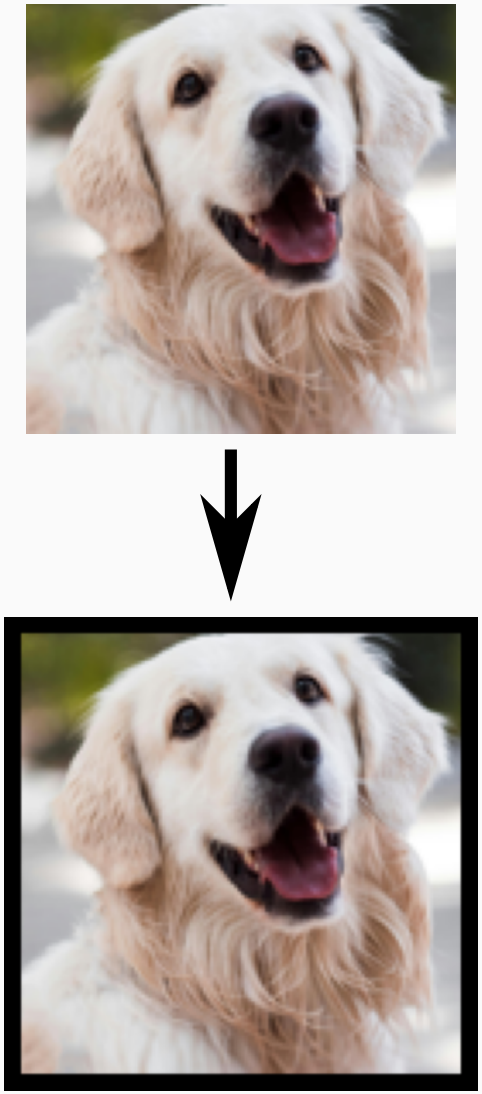
Pad the border of the image with a value

- Having a same size image
- Process border of the image

Zero padding

Padding with zero (border of image are set to zero)

$$\begin{pmatrix} a_{1,1} & a_{1,2} \\ a_{2,1} & a_{2,2} \end{pmatrix} \rightarrow \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & a_{1,1} & a_{1,2} & 0 \\ 0 & a_{2,1} & a_{2,2} & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$



Convolution summary

Convolution module/operator

Let be $s \in \mathbb{N}$ the stride (consider same stride along both axis), let be $x \in \mathcal{R}^{W_{in} \times H_{in} \times C_{in}}$ the input and $K \in \mathcal{R}^{W_{ker} \times H_{ker} \times C_{in} \times C_{out}}$ the kernel.

[0] Notice that we consider in the example the input padded

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$$W_{out} \leq \frac{W_{in} - W_{ker}}{s} + 1$$

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($H_{out} \in \mathbb{N}$). Thus, $O \in \mathbb{R}^{W_{out} \times H_{out} \times C_{out}}$

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Convolution module/operator

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$$O_{i,j,l} = \sum_{n=0}^{W_{ker}} \sum_{m=0}^{H_{ker}} \sum_{k=0}^{C_{in}} x_{((i-1)\times s+1+n,(j-1)\times s+1+m,k)} K_{n,m,k,l}$$

- **Stride:** Window shift between each step (number of pixels)
- **Padding:** Involves adding extra pixels around the border of the input feature map before convolution

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Convolutional Neural Networks: Pooling operation

Objectives

- Select most relevant part of the features map

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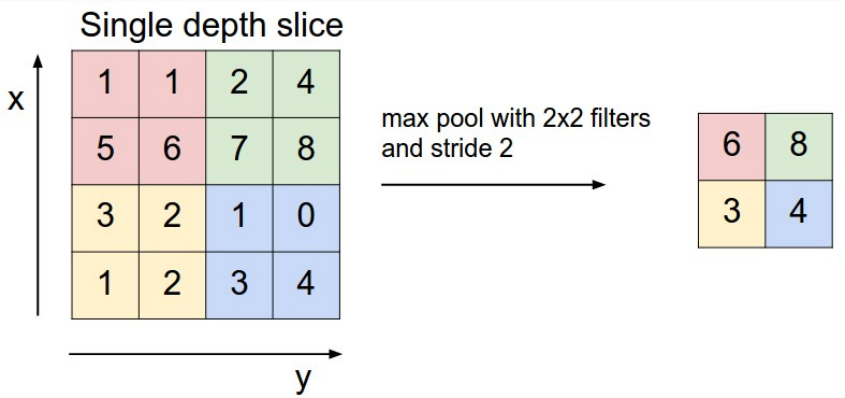

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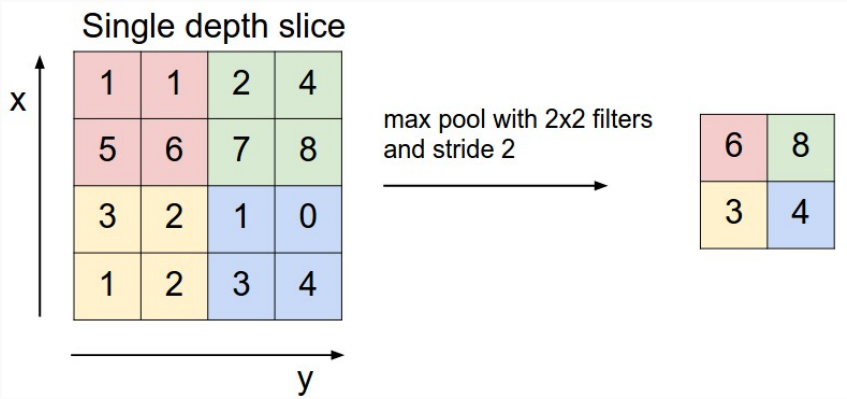

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Average Pooling

Window averaging on features maps

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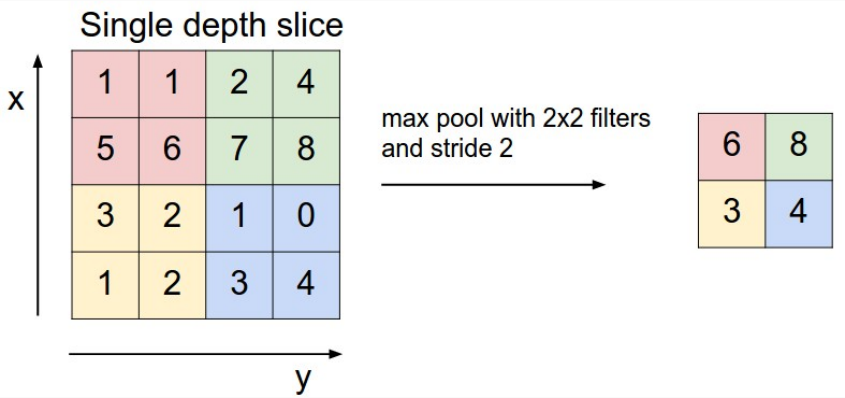

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Max Pooling

Window maximum on features maps

$$O_{i,j,l} = \max_{n,m} x_{((i-1)\times s+1+n,(j-1)\times s+1+m,l)}$$

Convolutional Neural Networks: Whole architecture

Convolutional neural network architecture

- Alternate pooling and convolution (with non linear activations)

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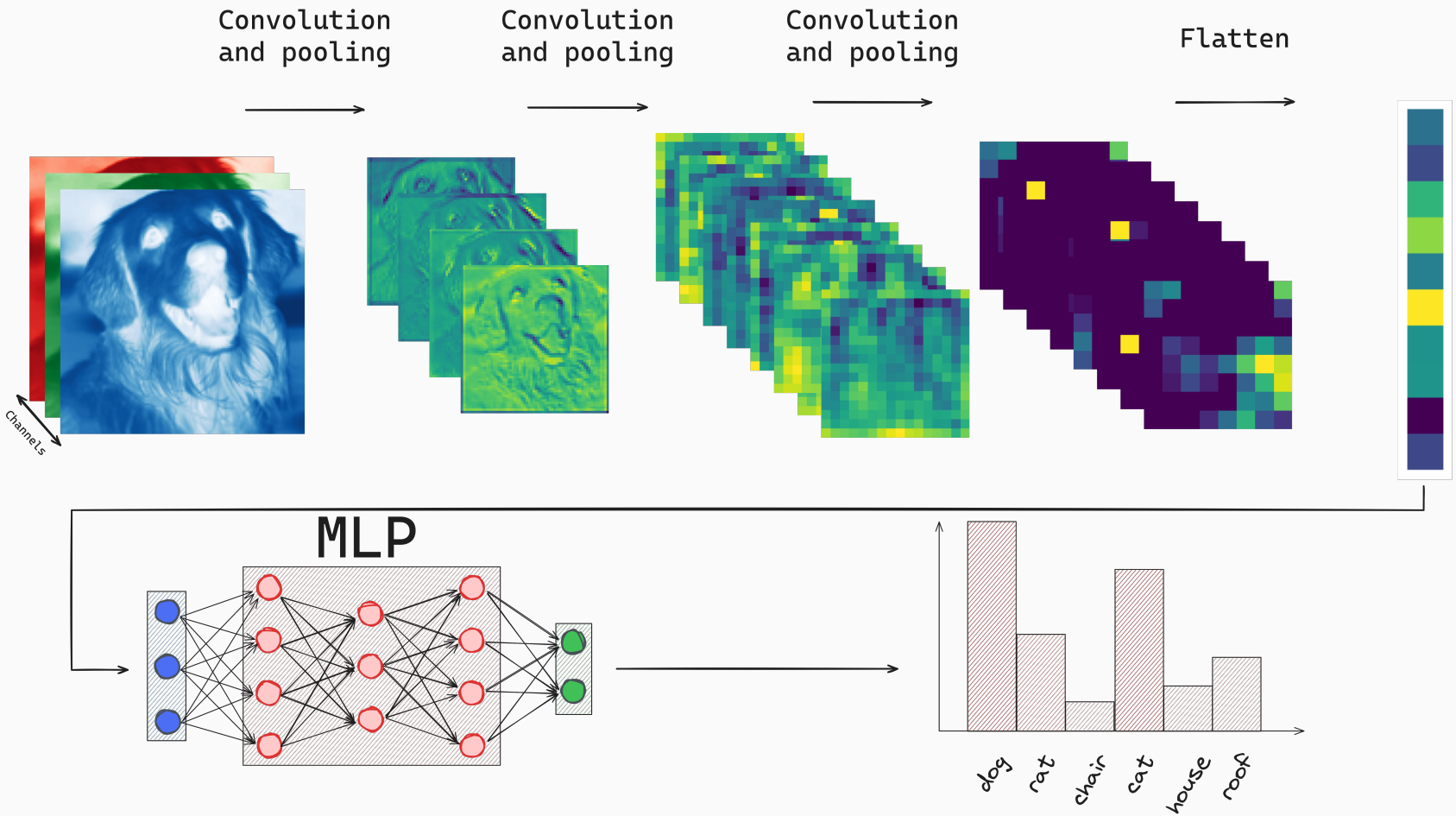
Convolutional neural network architecture

- Alternate pooling and convolution (with non linear activations)
- At a certain layer $\rightarrow$ flatten features map to get a 1 dimensional vector
- Use a classical MLP to predict the class (also called a Feed-Forward network)

Convolutional Neural Network



The VGG-16 architecture

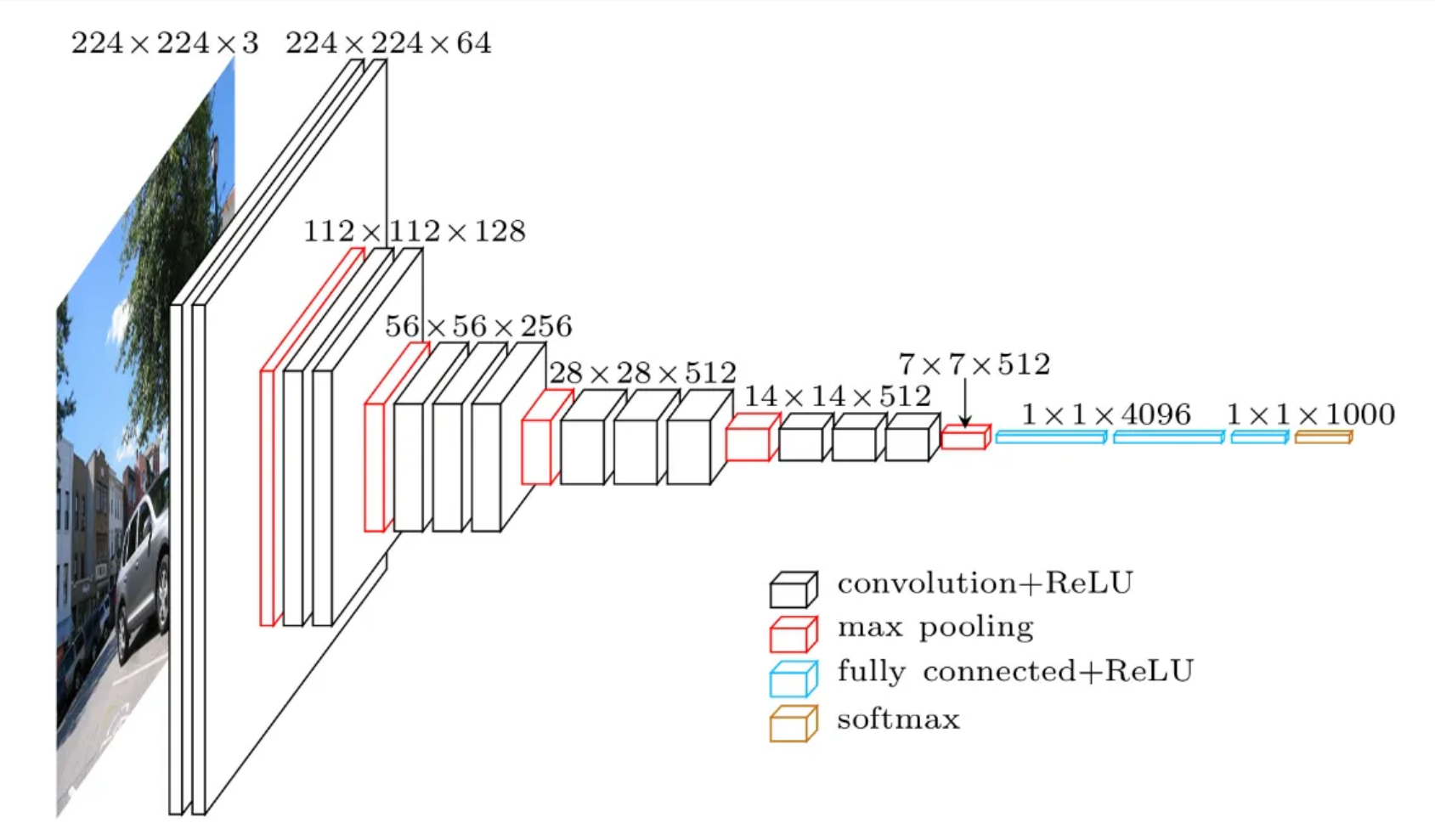


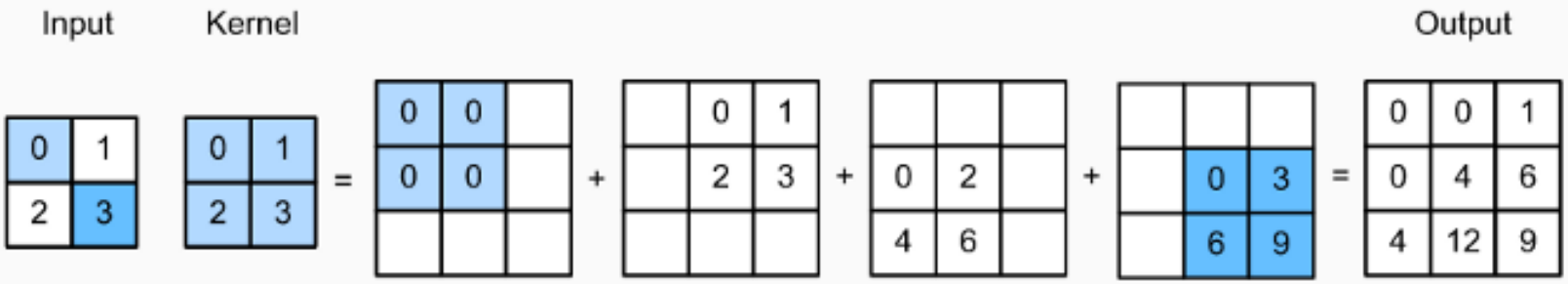
Figure 1: The VGG16 (Visual Geometry Group) CNN[1]

[1] https://lekhuyen.medium.com/an-overview-of-vgg16-and-nin-models-96e4bf398484

Image generation?

$\rightarrow$ Generate images using "inverse" convolution layers

Main idea:



(see deconvolution or transposed convolution layers)

Exercises

Implementation Of CNN

- Implement Convolution function
- Use pytorch to implement a CNN
- Comparison of the results

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