Plan du cours

1) Introduction au machine learning

2) Régularisation et forêts aléatoires

3) Réseau de neurones

4) Réseau de neurones convolutifs

Pour chaque séance:

1h de cours / support transparent

2h de travaux pratiques (amener un ordinateur portable)

Perceptron et réseau de neurones

Les réseaux dense ou fully-connected on l'inconvénient d'avoir un nombre de poids très grand:

- Si image RGB de 5 x 5 pixels, on a $m = 3\times5\times5 = 75$ connections et poids par neurone de la première couche.
- Si image RGB de 1000 pixels on a $m = 3\times10^3\times10^3 = 3\times10^6$ poids par neurone à calculer. Inutilisable pour plusieurs neurones et plusieurs couches.

Une solution à ce problème a été apportée par les réseaux de neurone convolutif (CNN, convolutionnal neural network).

Ces réseaux utilise la notion de convolution en traitement du signal.

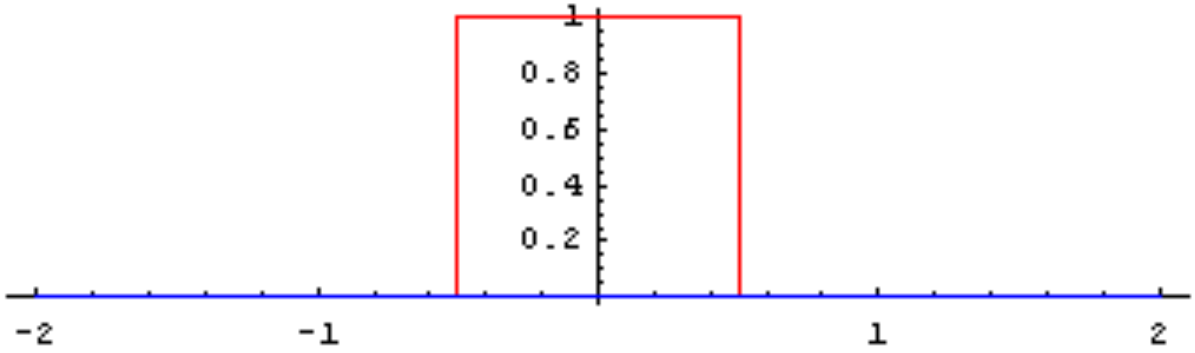
Réseaux de neurone convolutif

En traitement du signal une convolution de deux fonctions est définit par :

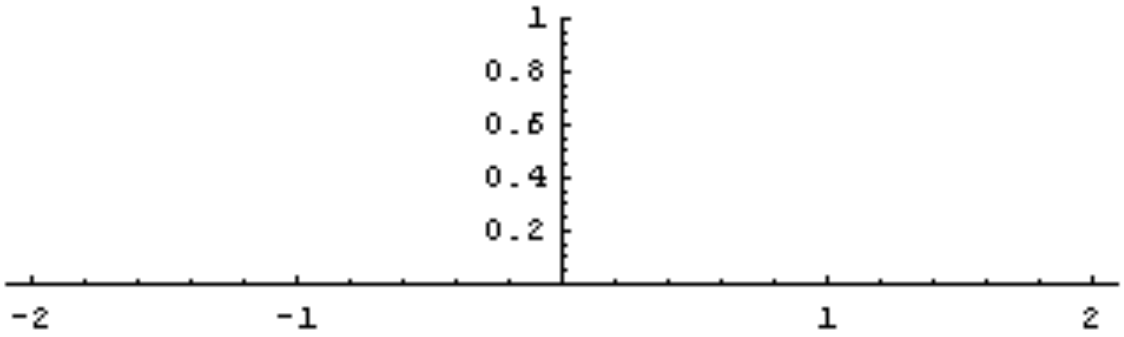
$$(f * g)(t) = \int_{-\infty}^{\infty} f(t-\tau)g(\tau)d\tau$$

f et g

Fonction porte
=1 si $-{}^{1}/_{2} < x < {}^{1}/_{2}$
=0 sinon



$f * g$



Filtre 1D

On utilise classiquement en climatologie des filtres pour lisser des séries temporelles.

$$f'(t_i) = \sum_{k=-N}^{N} f(t_{i-k}) w_{N-k+1}$$

Les paramètres $w_{1 \leq i \leq 2N+1}$ forment un noyau ou kernel

$2N + 1$ est la taille du filtre

Exemple :

$w_i = \frac{1}{2N+1}$ forme la moyenne glissante sur une fenêtre de $2N + 1$ pas de temps.

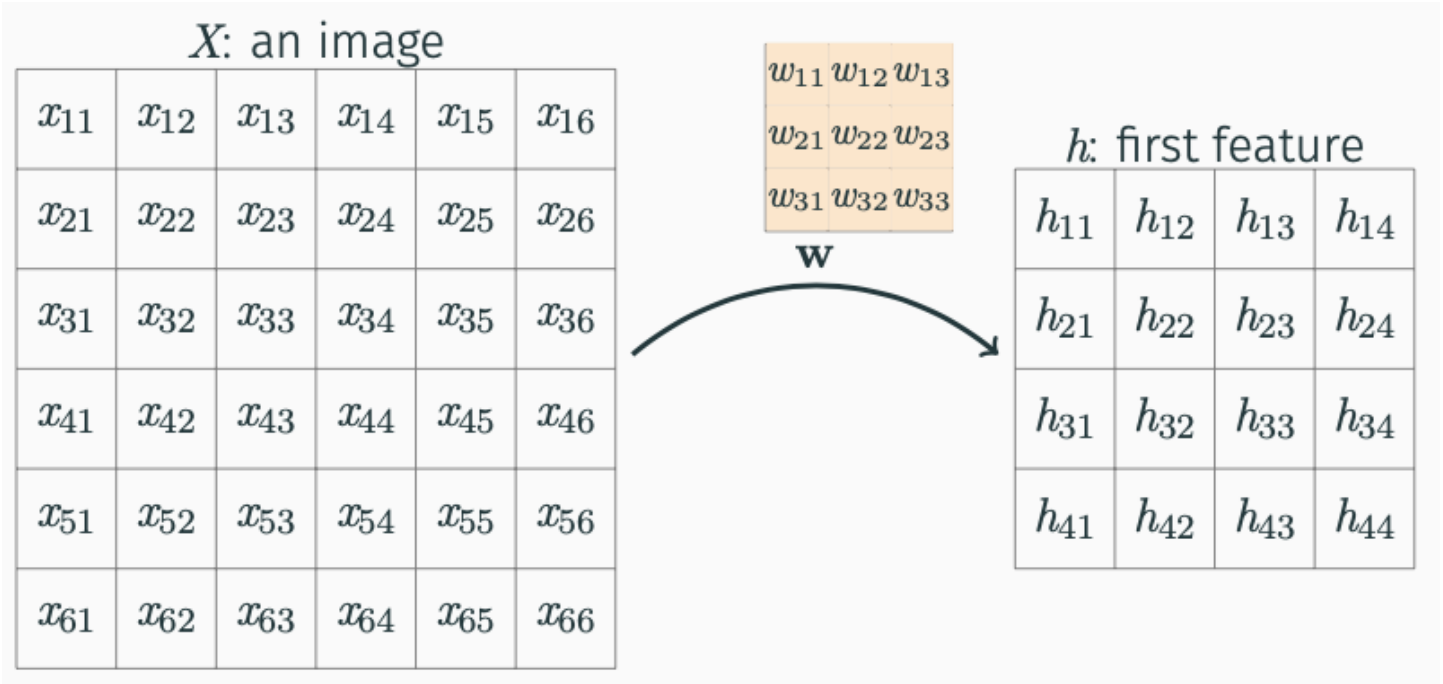
Il existe des filtres avec des meilleurs propriétés, comme les filtres de Butterworth ou Lanczos.

Filtre 2D

On utilise classiquement des filtres mettre en avant certaines caractéristiques de l'image.

Exemple : filtre de taille 3 x 3

$$h_{i,j} = \sum_{k=1}^{3} \sum_{l=1}^{3} x_{i+k-1,j+l-1} w_{k,l}$$



Filtre 2D

Input

Edge detection

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Box mean

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Sharpen

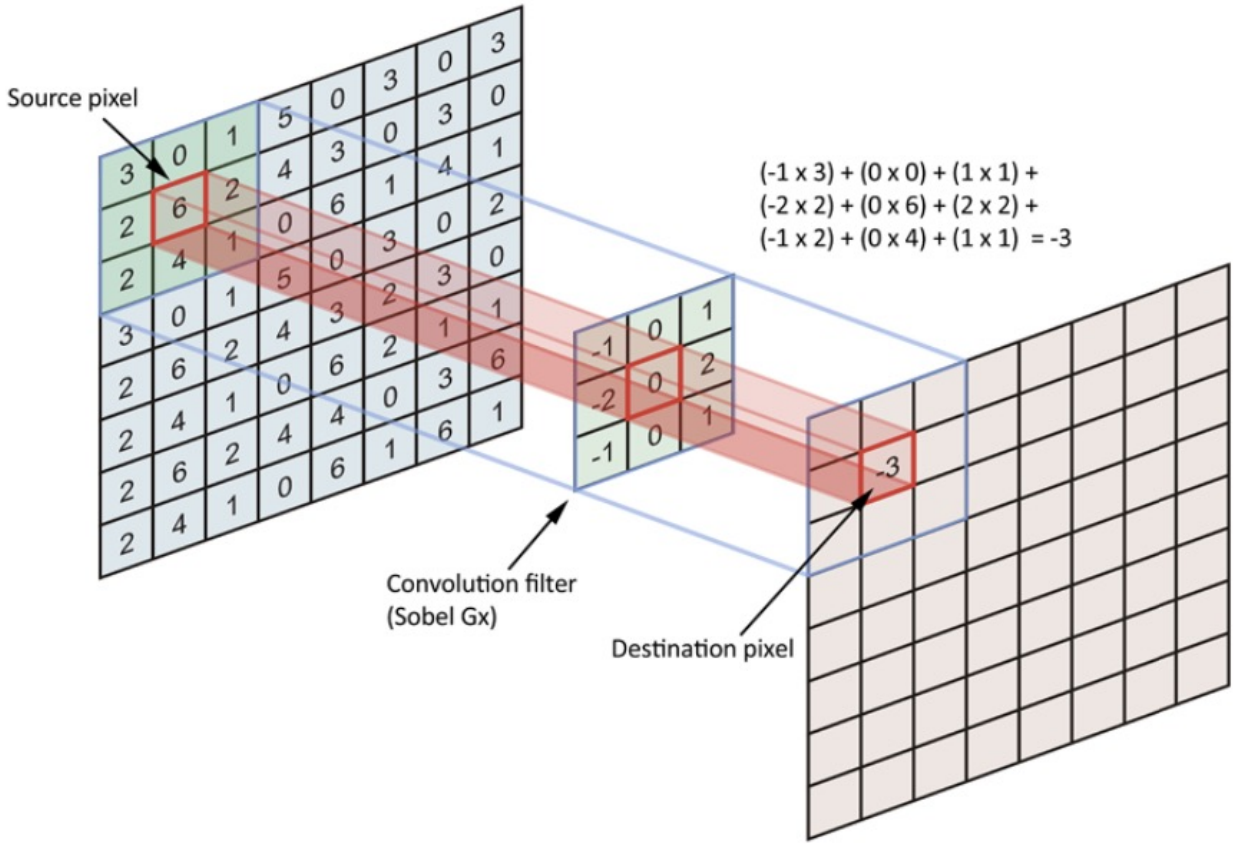
$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

Gaussian blur

$$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

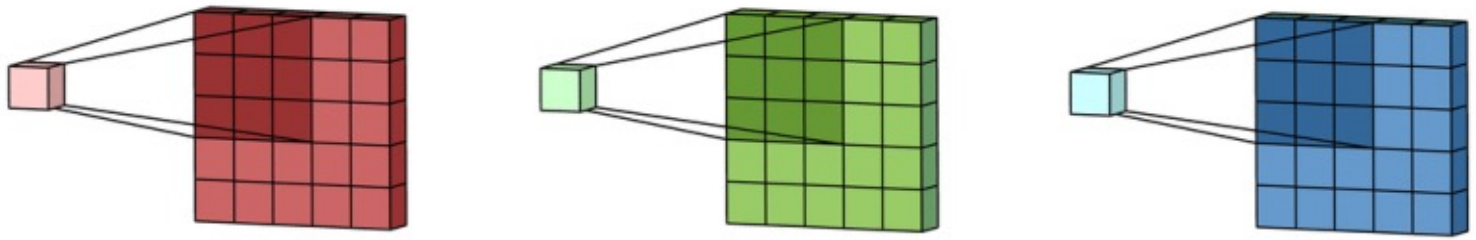
Filtre 2D

Dans un CNN (Convolutional Neural Network), les poids correspondent au kernel. Cela permet d'extraire certaines caractéristiques de l'image.



Summary of Convolutional layer steps

1. Convolution



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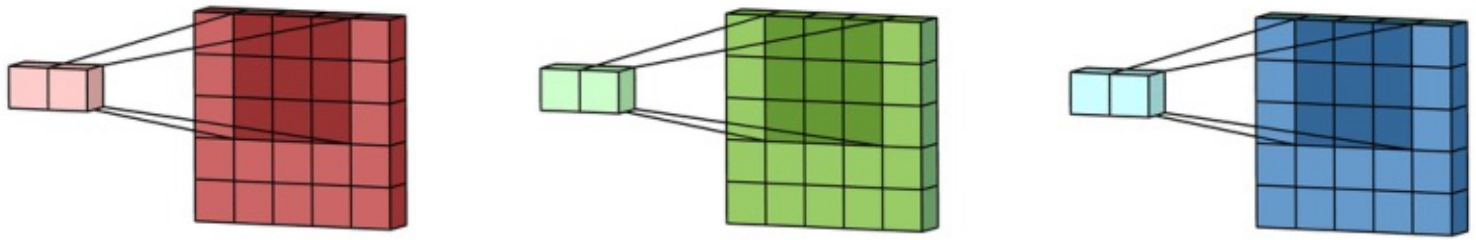

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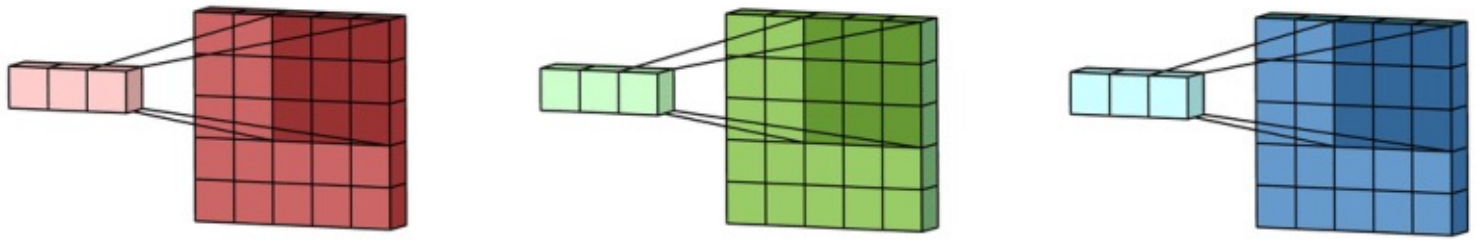

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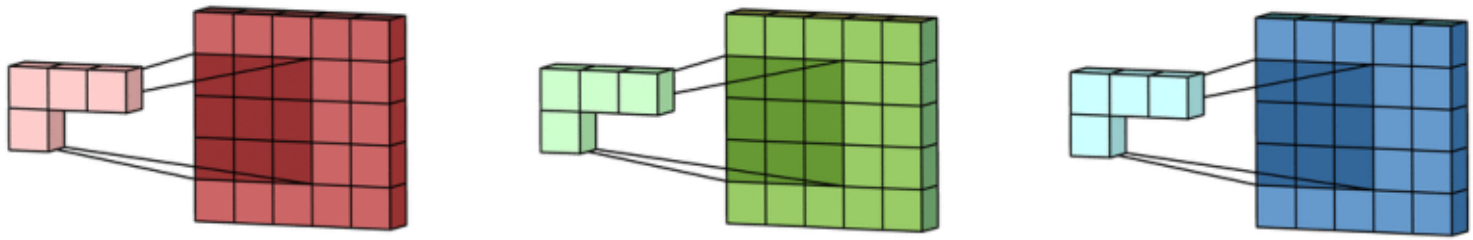

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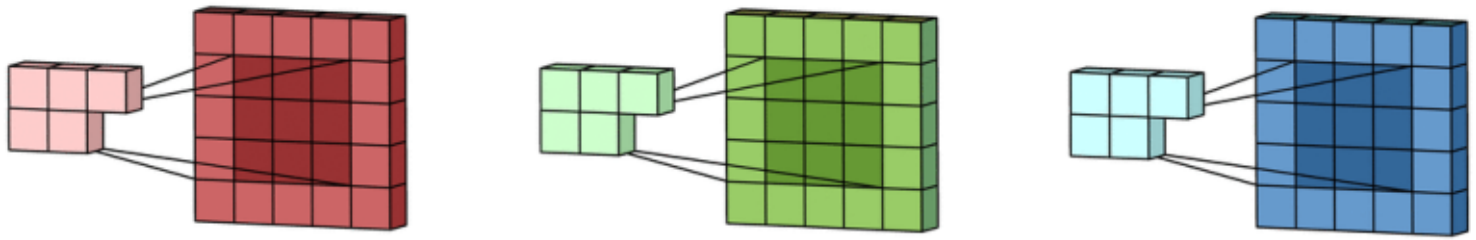

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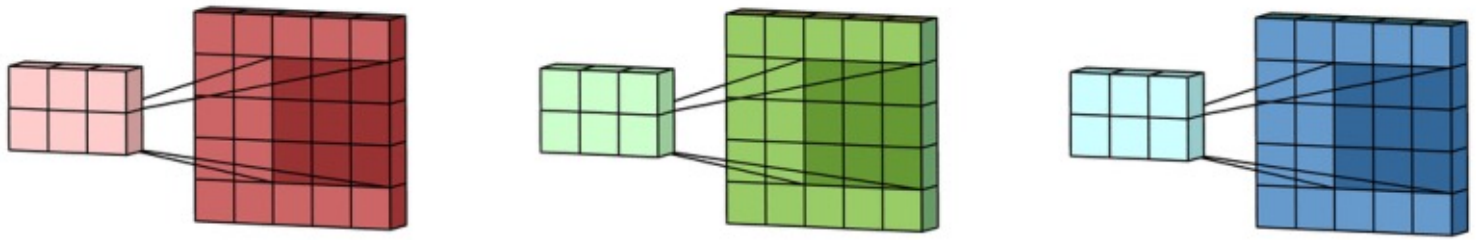

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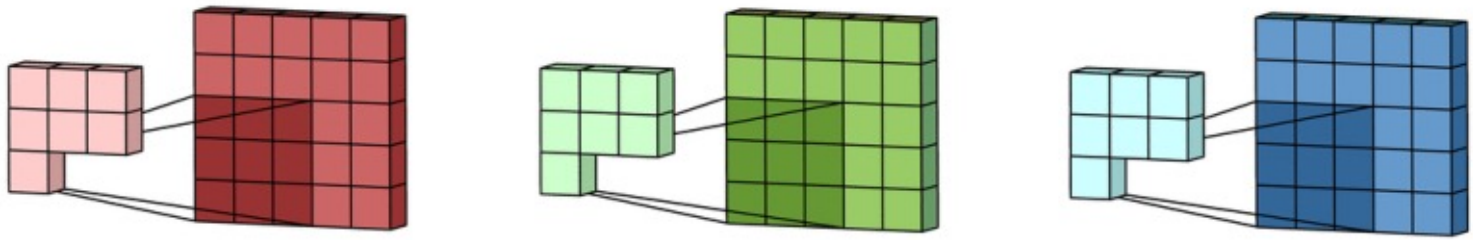

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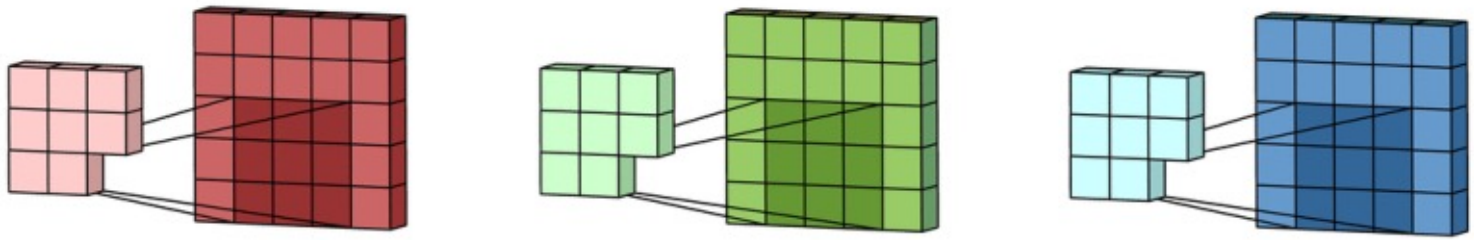

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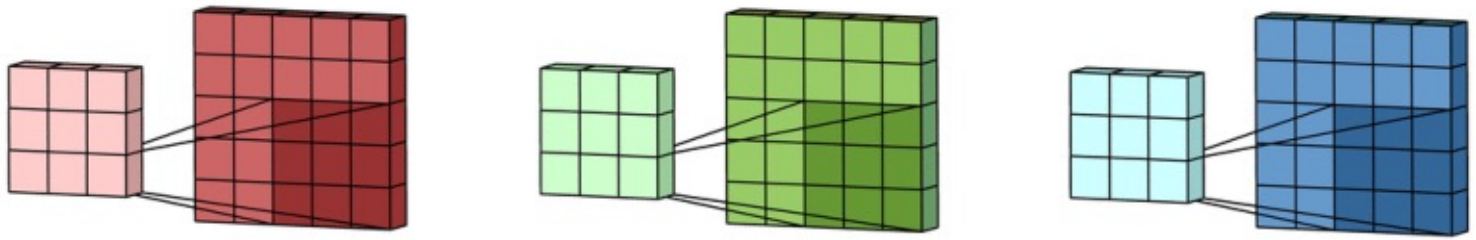

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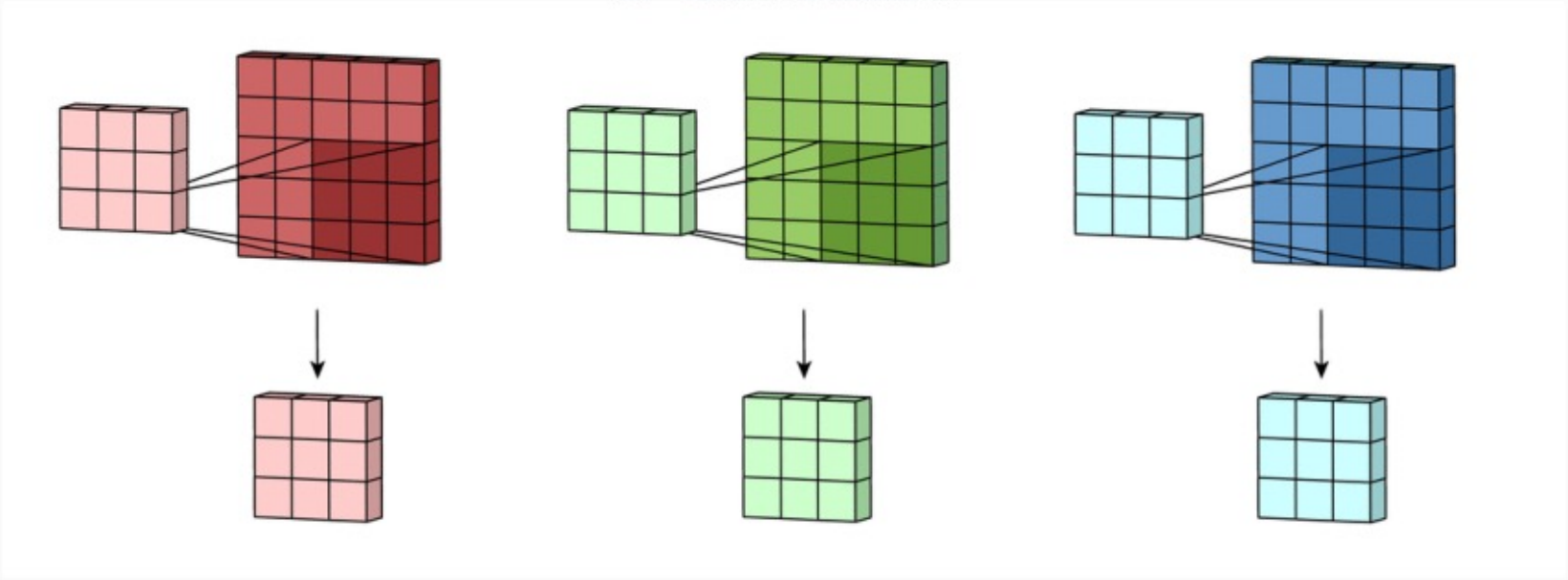

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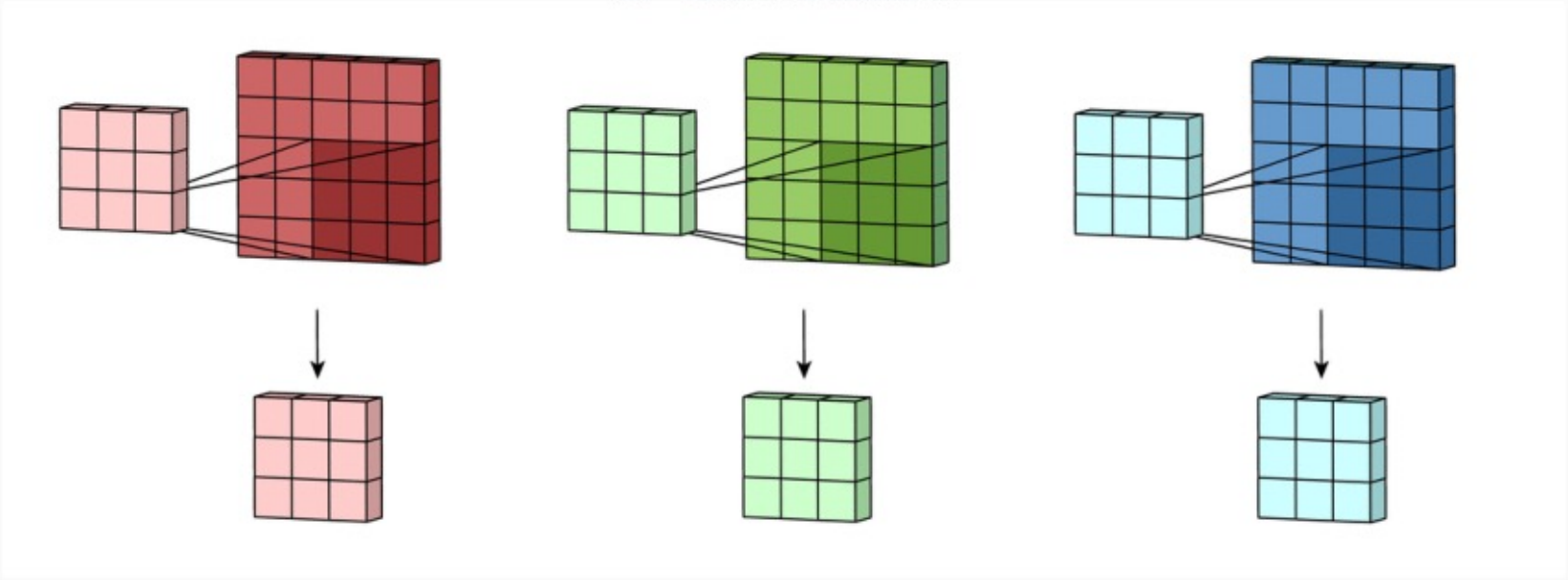

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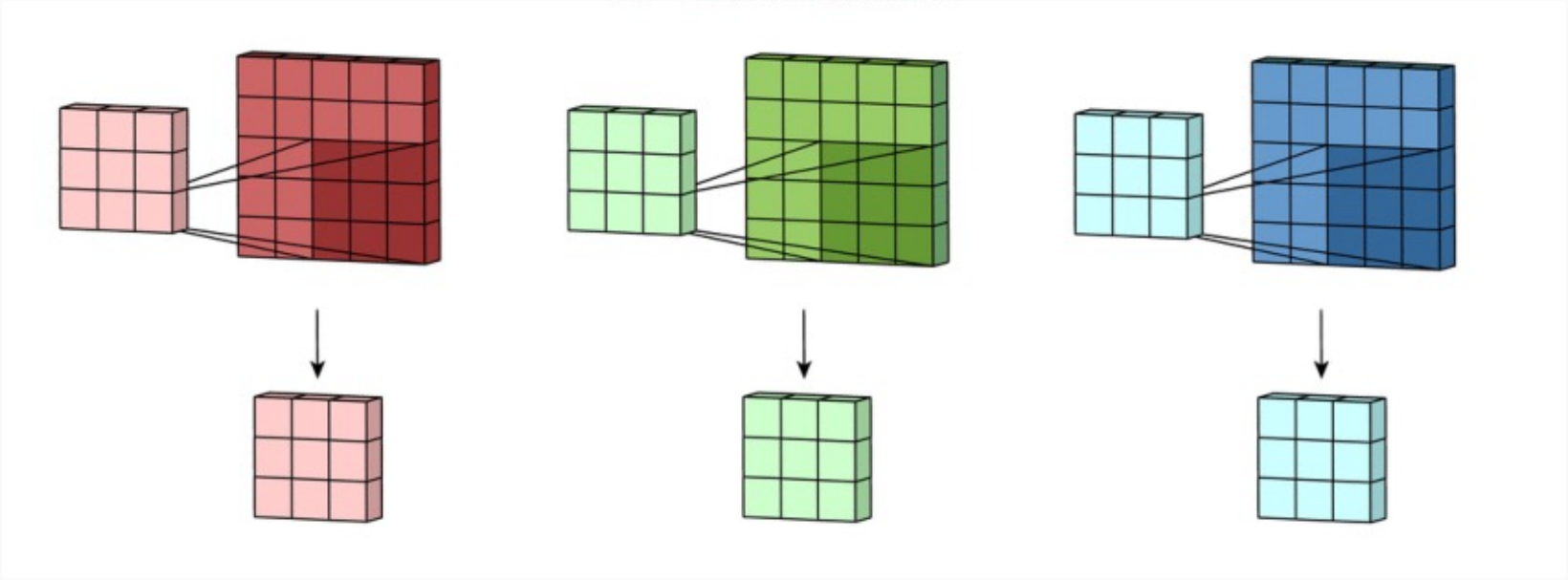
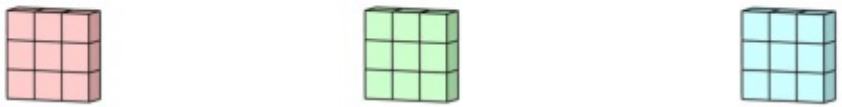


2. Addition



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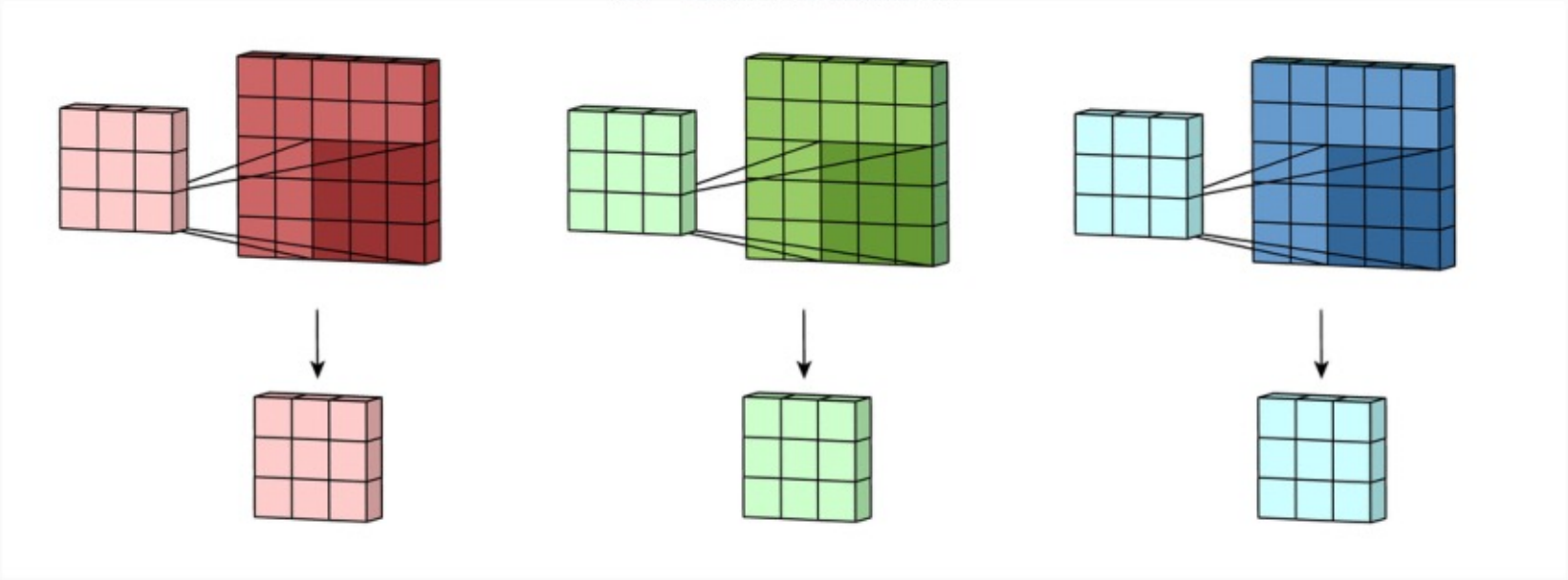

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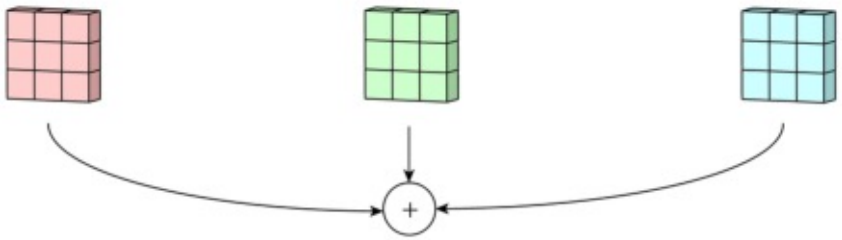

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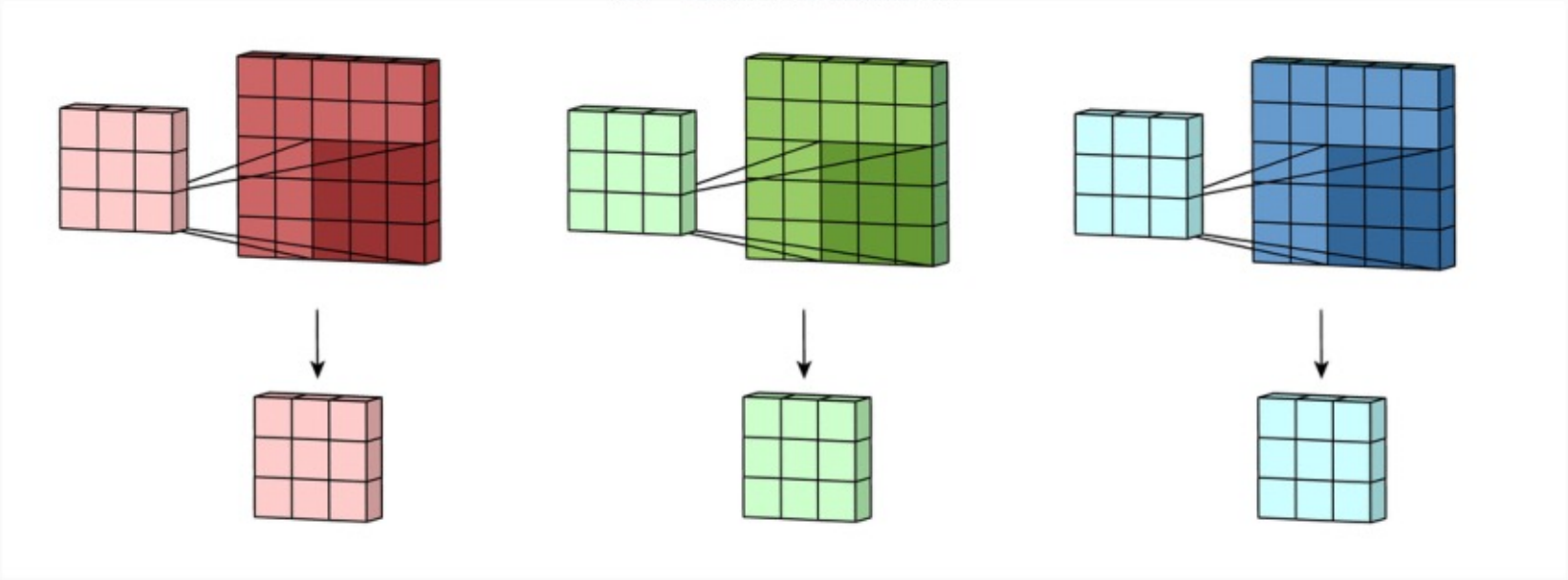

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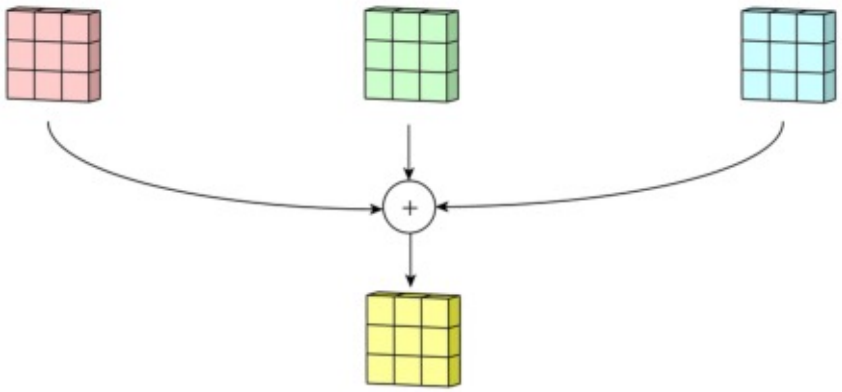

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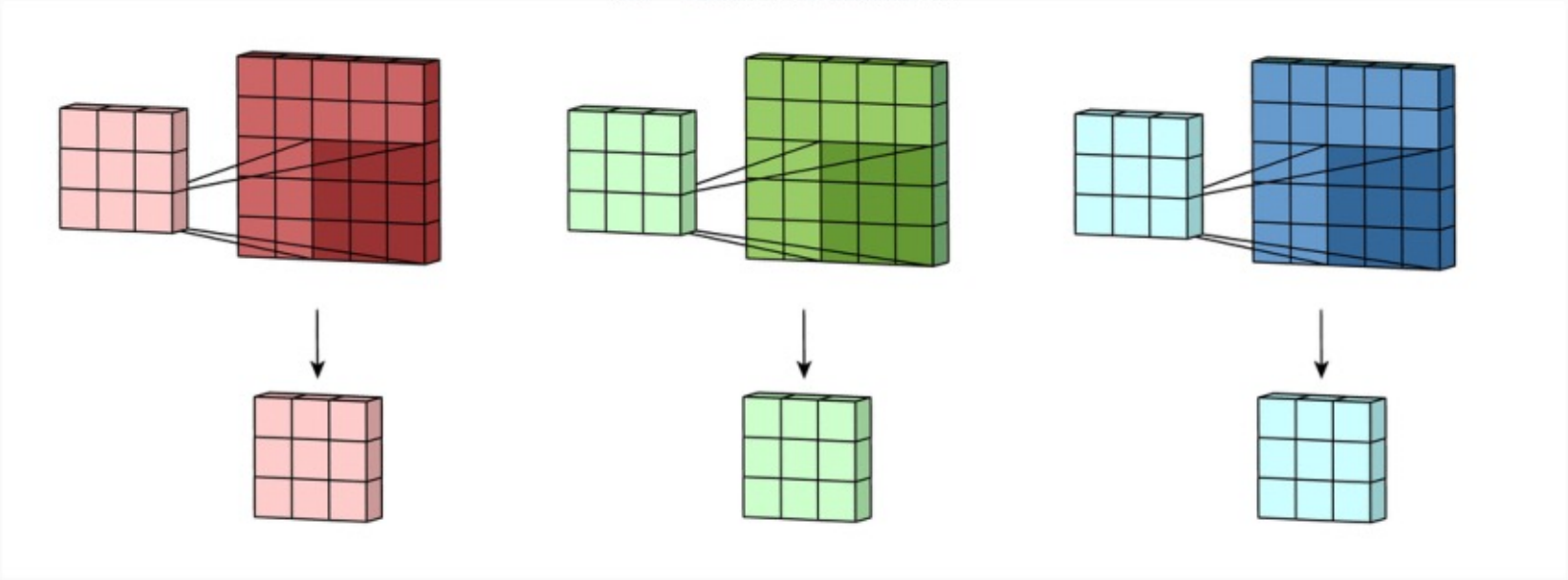

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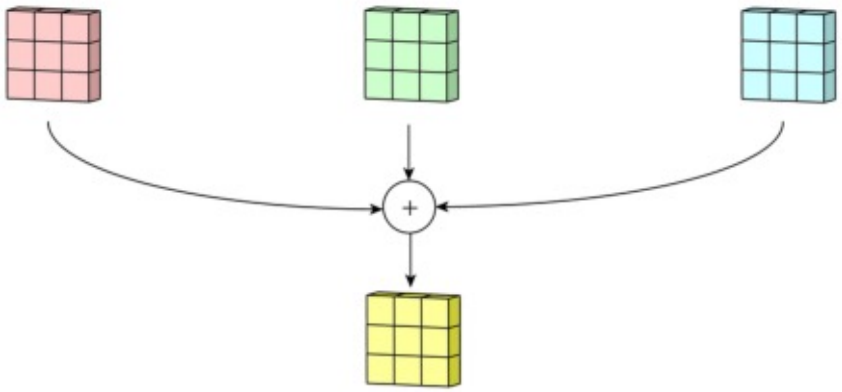

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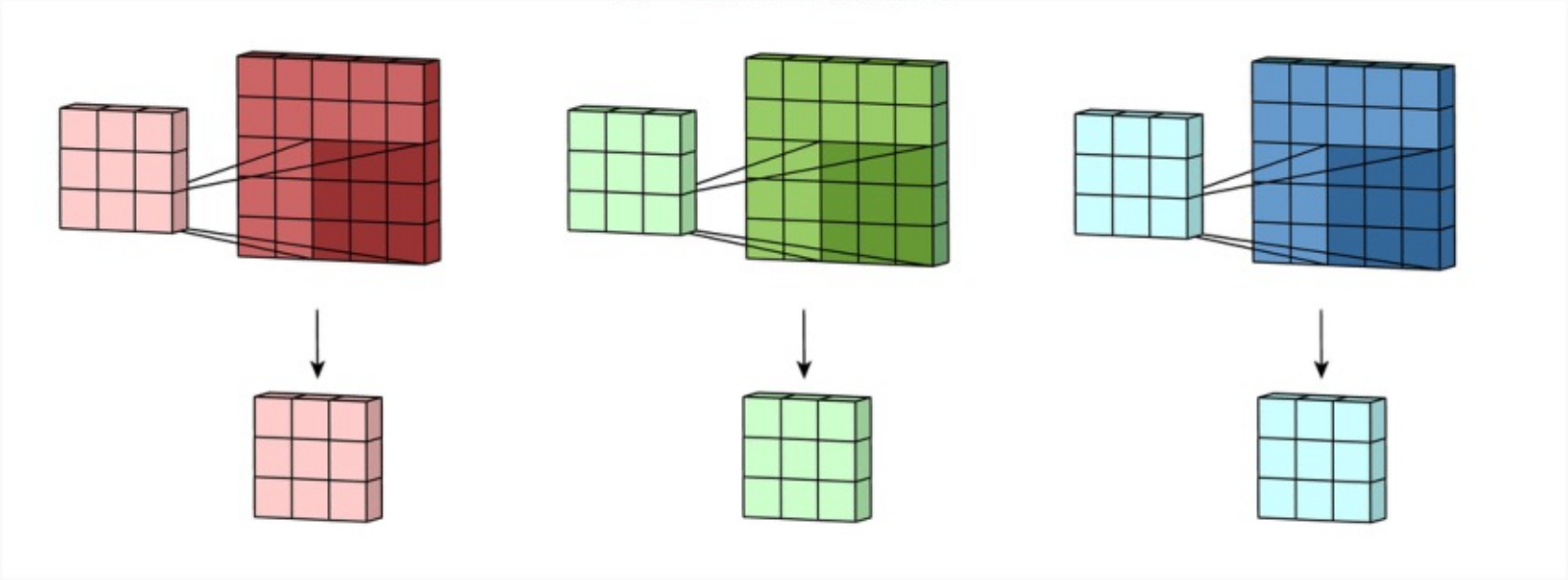

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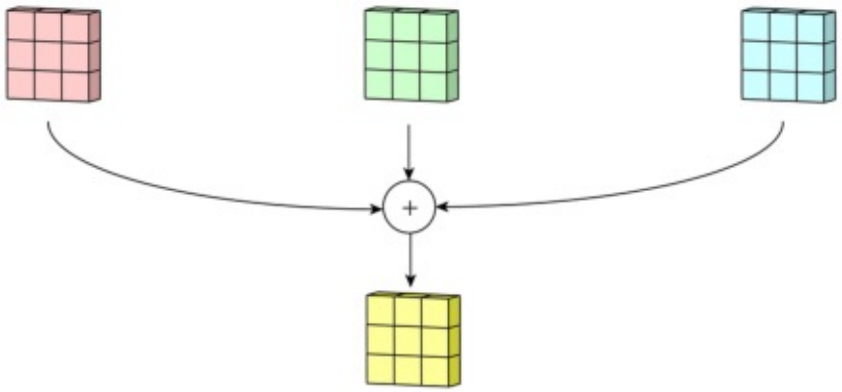

3. Bias

Summary of Convolutional layer steps

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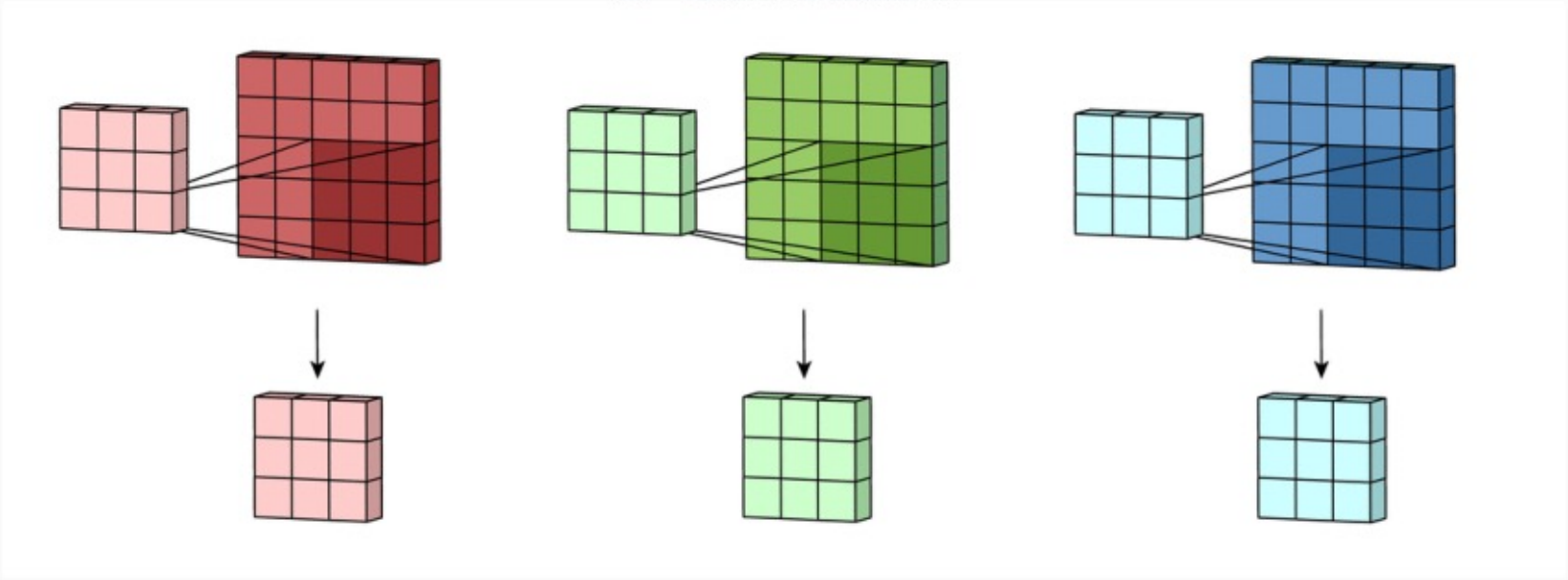

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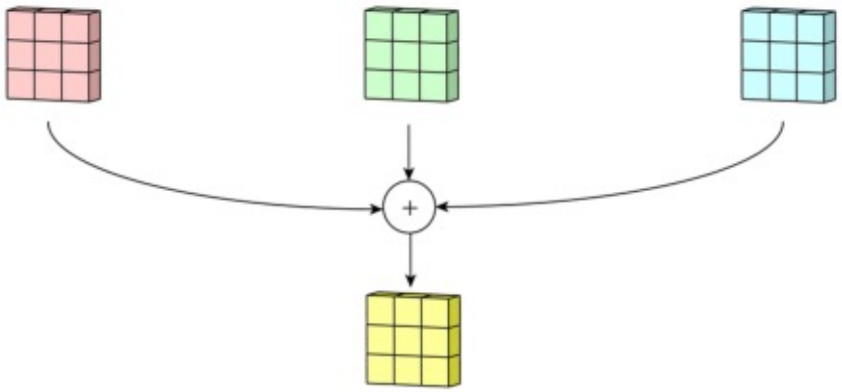

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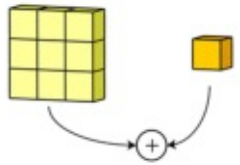

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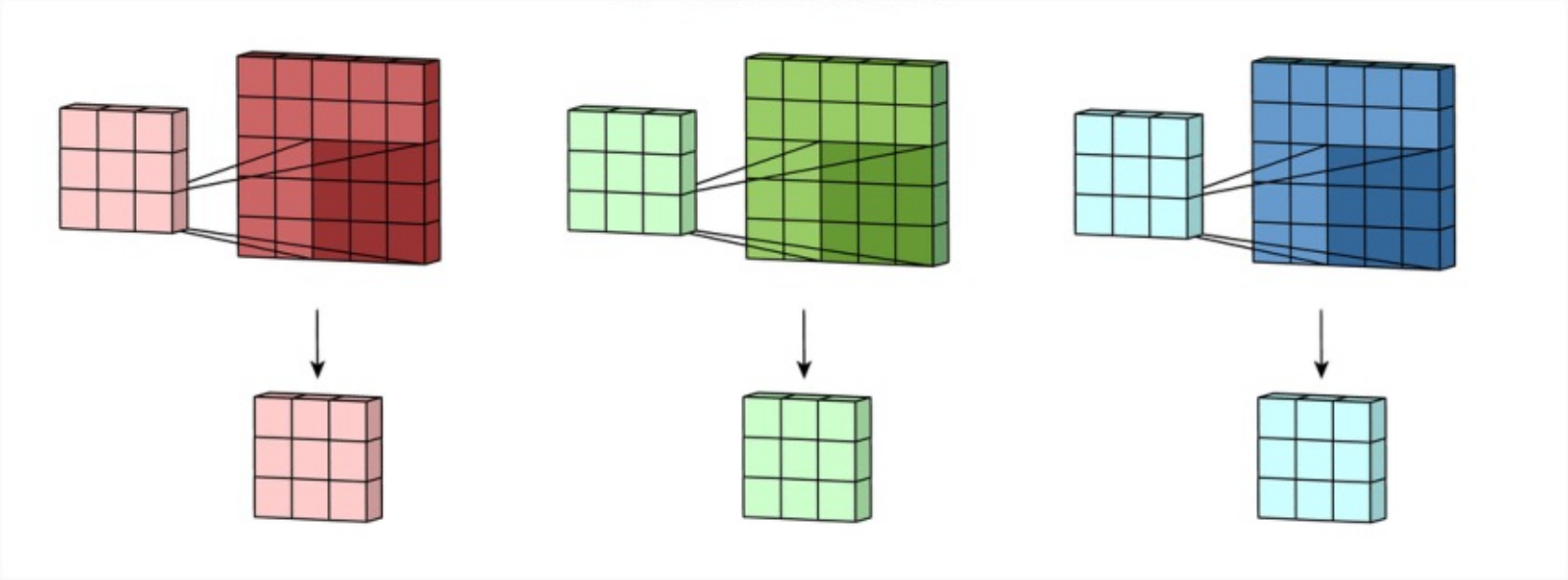

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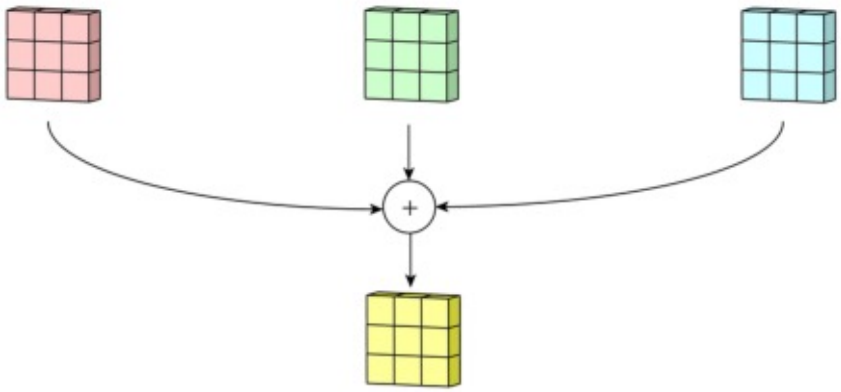

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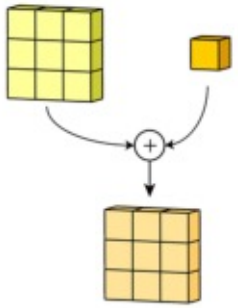
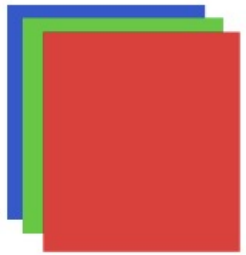
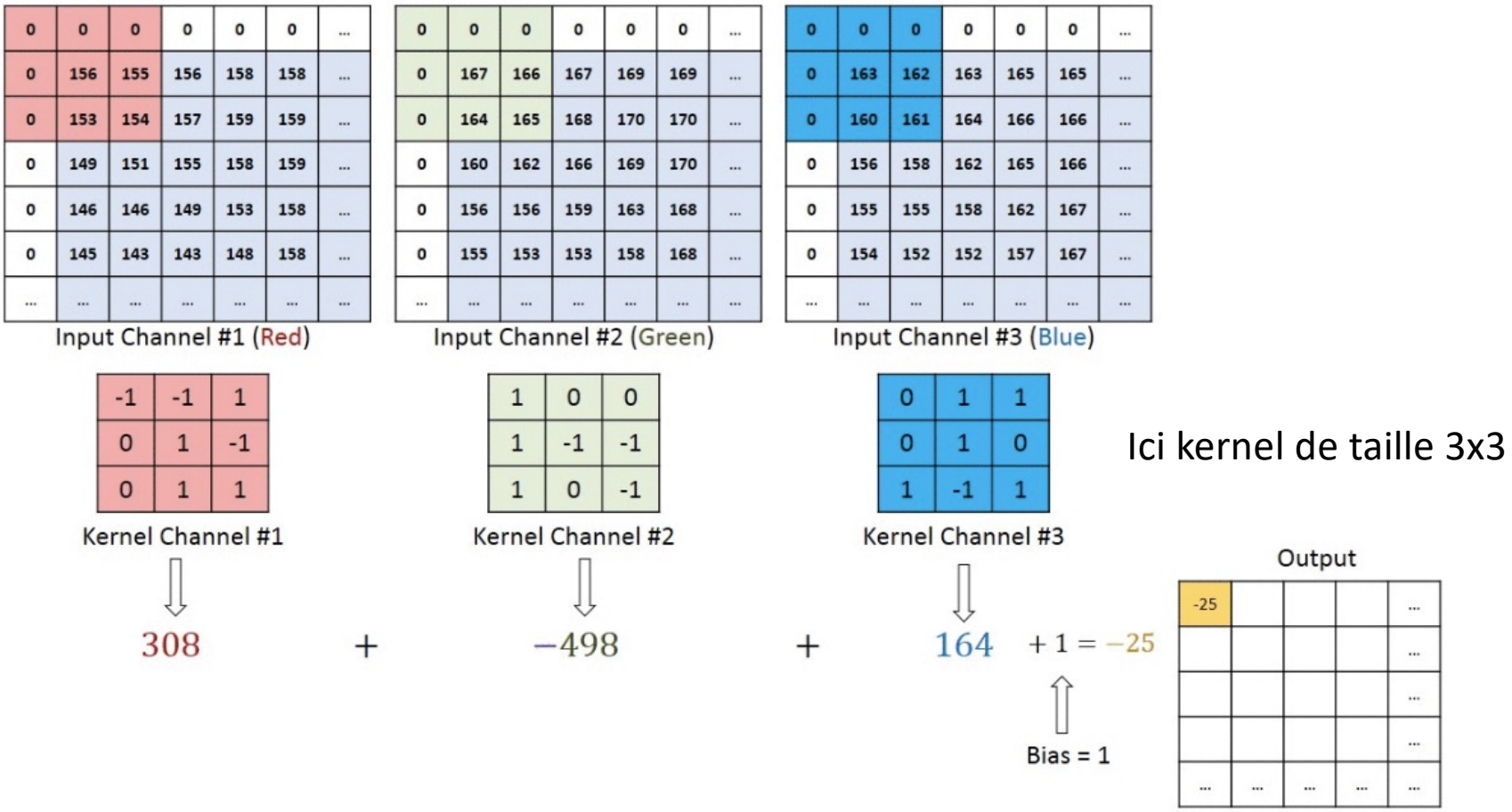


Cas d’un input 3D

RBG



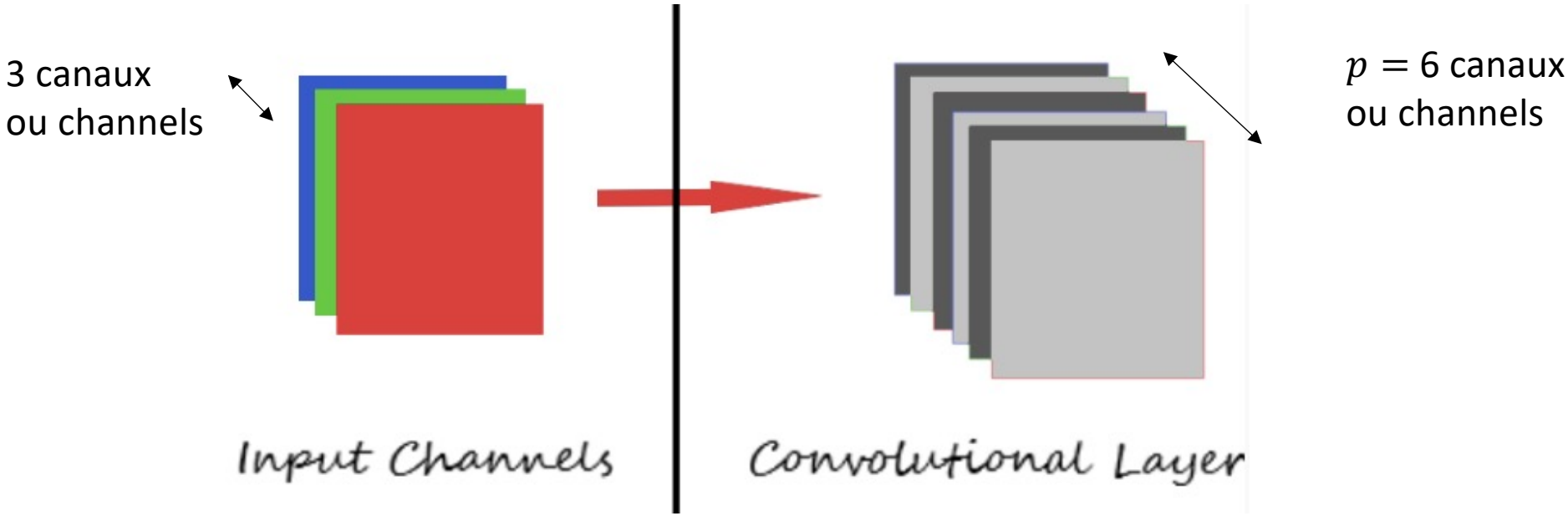
On applique un kernel différent à chaque canaux.



Ici kernel de taille 3x3

Principaux paramètres

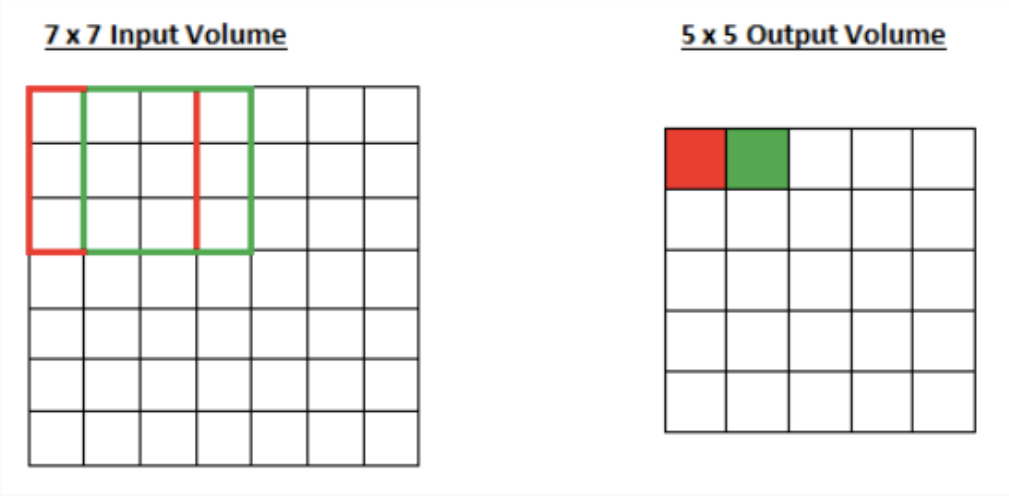
- $K =$ taille des kernels
- $p =$ Nombres de canaux de sorties



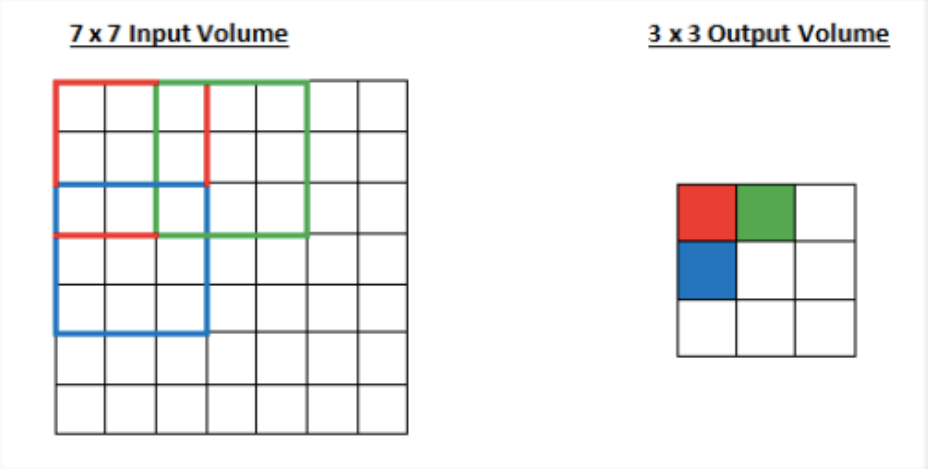
Principaux paramètres

- $K =$ taille des kernels
- $p =$ Nombres de canaux de sorties
- $S =$ Stride

$S = 1$

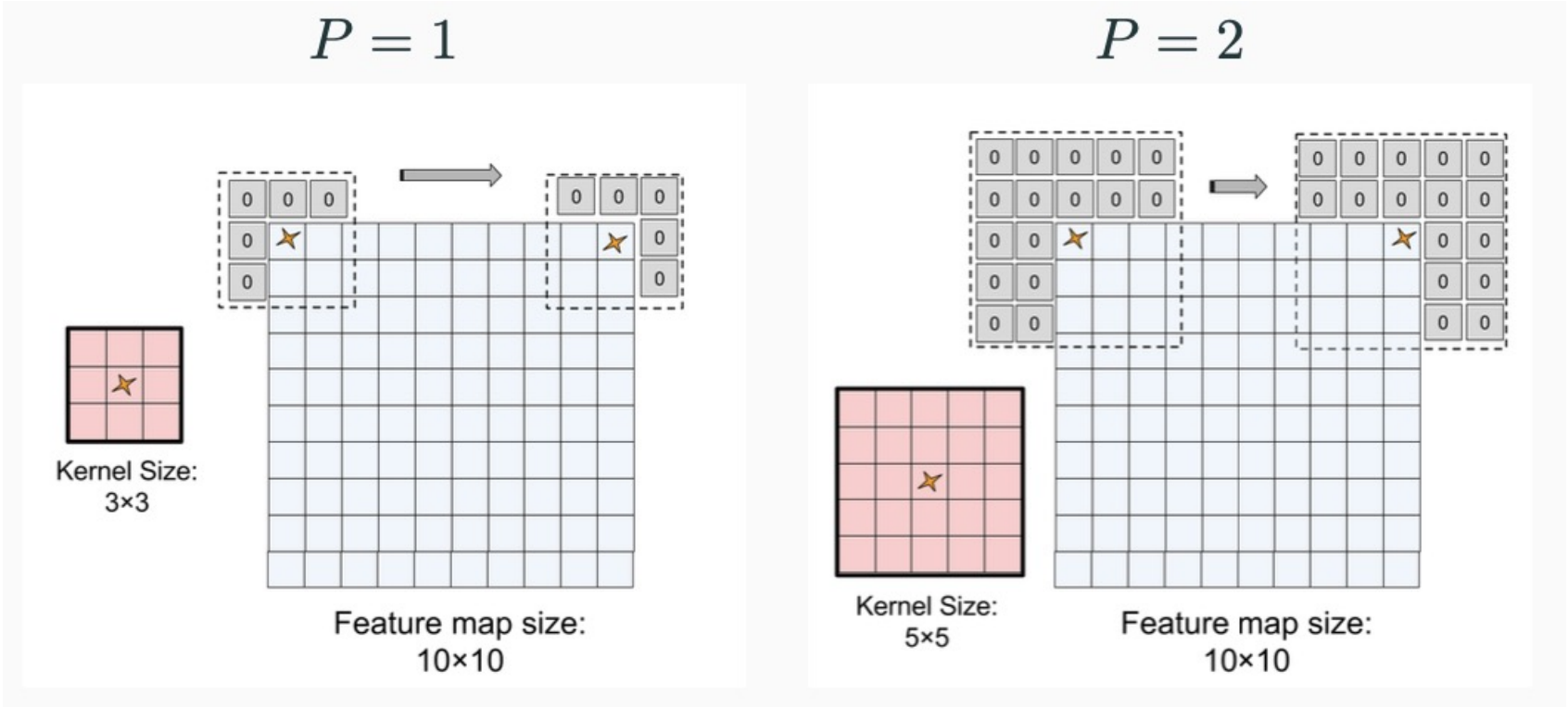


$S = 2$



Principaux paramètres

- $K =$ taille des kernels
- $p =$ Nombres de canaux de sorties
- $S =$ Stride
- $P =$ Padding



Principaux paramètres

- $K =$ taille des kernels
- $p =$ Nombres de canaux de sorties
- $S =$ Stride
- $P =$ Padding

Si on a: N_{in} : dimension de l'image d'entrée
N_{out}: dimension de l'image de sortie

Alors:

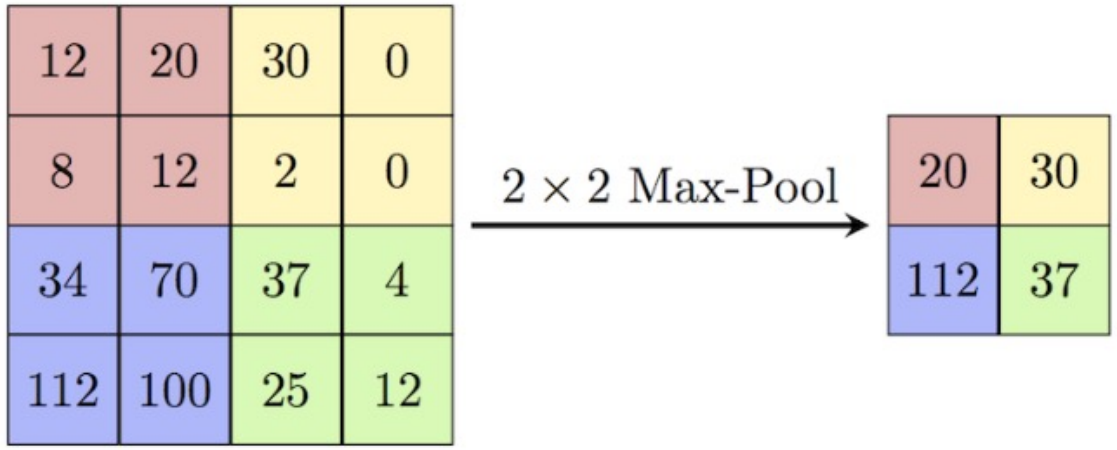
$$N_{out} = \frac{N_{in} - K + 2P}{S} + 1$$

Quelques remarques

- les couches convolutives agissent au niveau local,
- les poids sont invariants par translation (ils ne dépendent pas de la localisation),
- Les CNNs peuvent utiliser des images de taille différente.

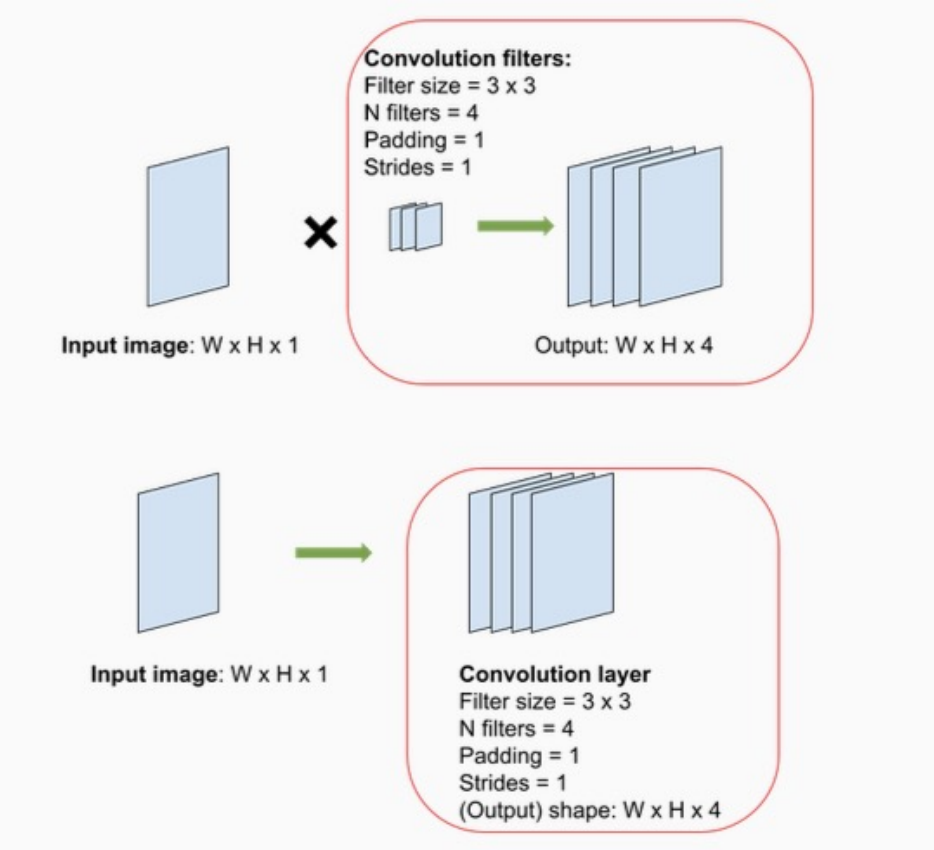
Maxpool

Une transformation Maxpool est alors appliqué pour réduire la taille de l'image, tout en conservant les gradients.

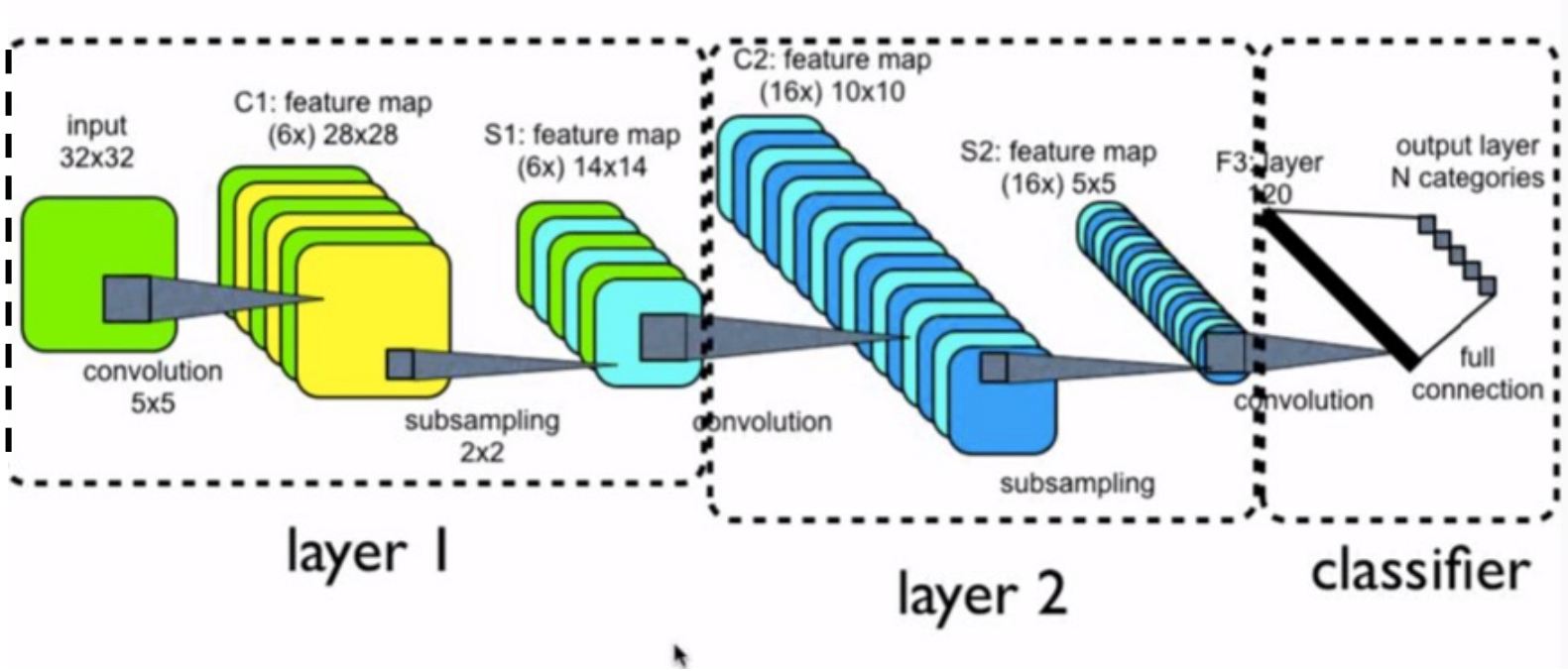


Quelques remarques

- Une opération de convolution est souvent schématisée par une couche convolutives et en faisant apparaître les paramètres de padding, stride, taille des kernels, nombre de canaux.



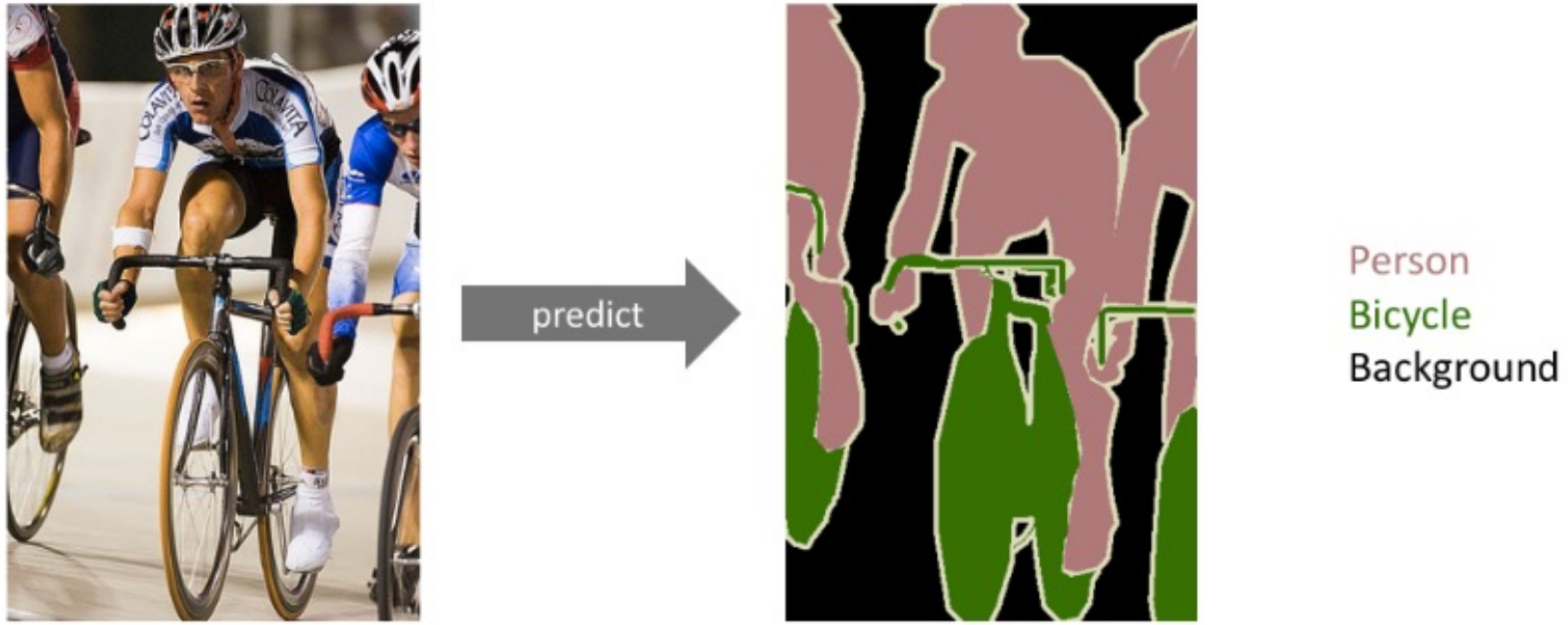
Exemple de classification



Ce réseau peut répondre à la question : est-ce que l'image appartient à la catégorie k avec $k \in [\![0, N]\!]$? Exemple : Chien, chat ou canard?
On peut également faire de la régression. Exemple : à quel point l'image est-elle celle d'un chien?

Segmentation d’image

L’opération de segmentation consiste à produire une image où chaque partie de l’image est classifié.



Segmentation d’image

Chaque pixel d’une image est associé à un entier caractérisant une classe.

0: Background/Unknown
1: Person
2: Purse
3: Plants/Grass
4: Sidewalk
5: Building/Structures

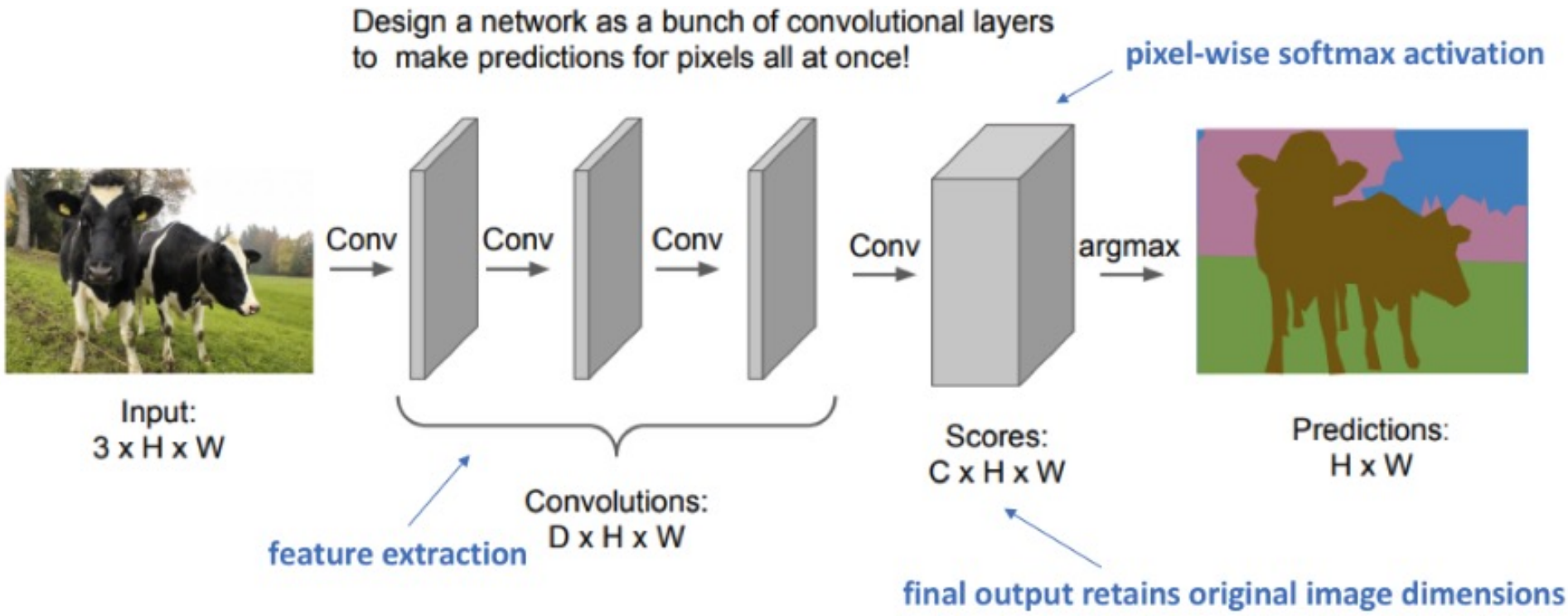
Loss function

Un fonction de coût performante est le coefficient de Dice (ou *Sørensen–Dice* ou *Dice similarity coefficient* DSC), qui mesure la similarité entre deux ensembles P et G.

$$DSC = \frac{2|P \cap G|}{|P| + |G|}$$

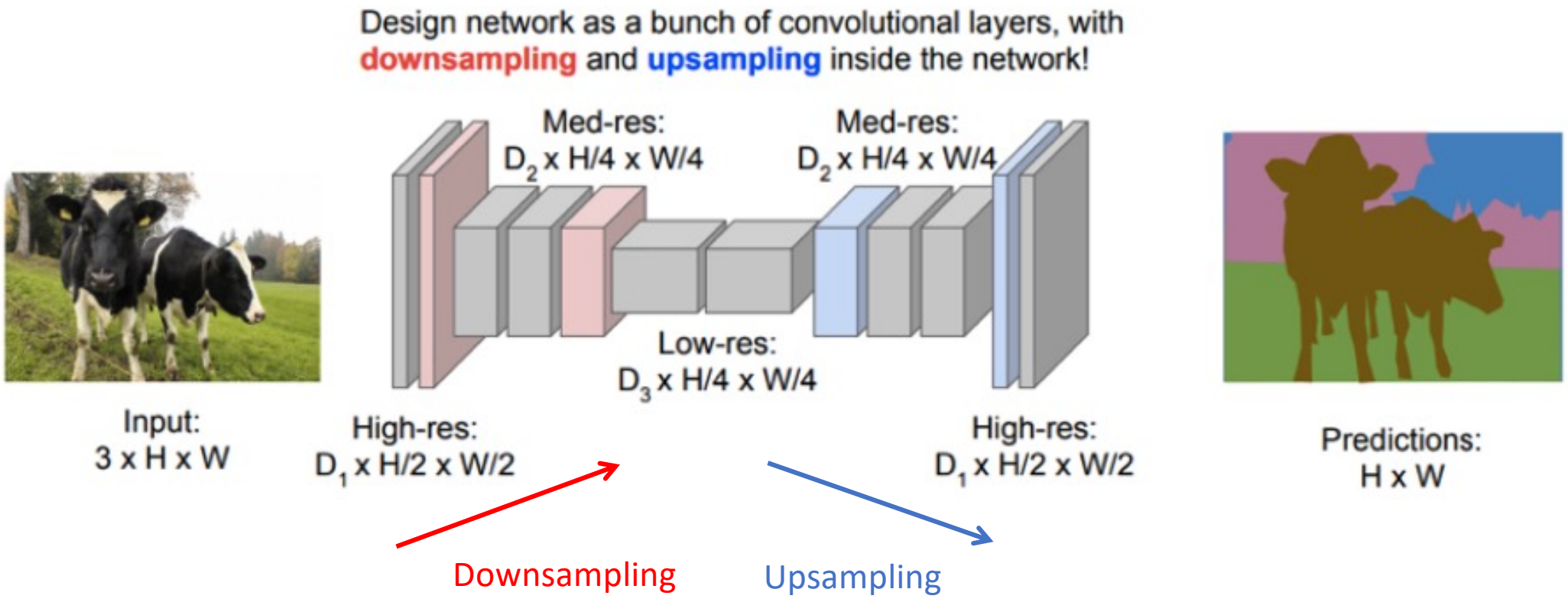
Approche par un CNN simple

Une approche simple consiste à réaliser une série de convolutions en conservant la taille de l'image.



Problème : en conservant la taille de l'image, l'apprentissage peut être long.

Approche plus performante



Avantage : l'apprentissage se fait à plus basse résolution pour les couches centrales.

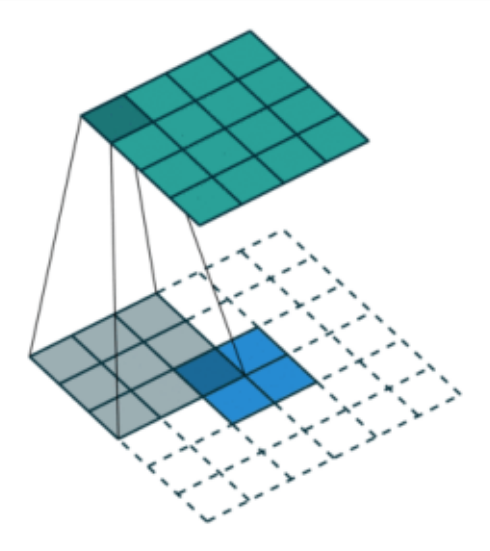
Upsampling-Downsampling

- Pour dégrader la résolution, on utilise du Maxpool (=downsampling)
- Pour retrouver la résolution originale de l'image, on utilise des couches convolutives avec du padding et ou un stride (upsampling).

Upsampling using "Transpose Convolution"

Often "Transpose Convolution" is used for upsampling. A convolution filter is applied to small input image with large padding and/or with strides. The example here shows: Padding = 2, Stride = 0.

Blue - input image, gray - filter, green - output image.



Images from fvisin Francesco

Upsampling using "Transpose Convolution"

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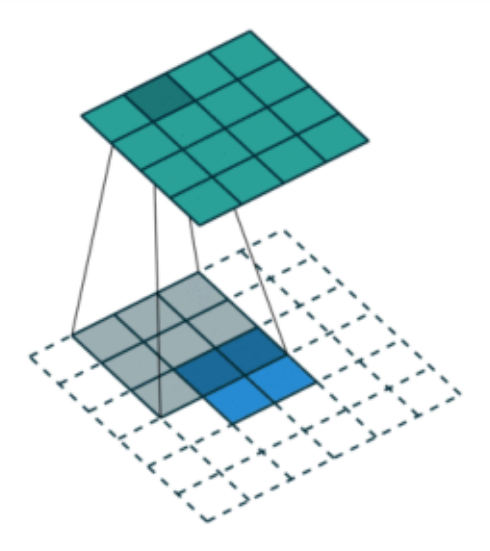

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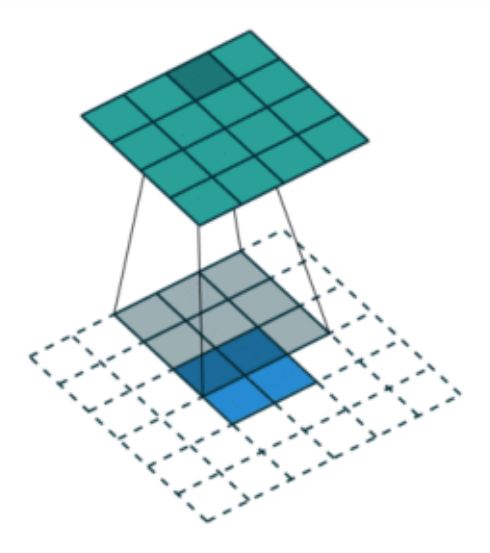

Images from fvisin Francesco

Upsampling using "Transpose Convolution"

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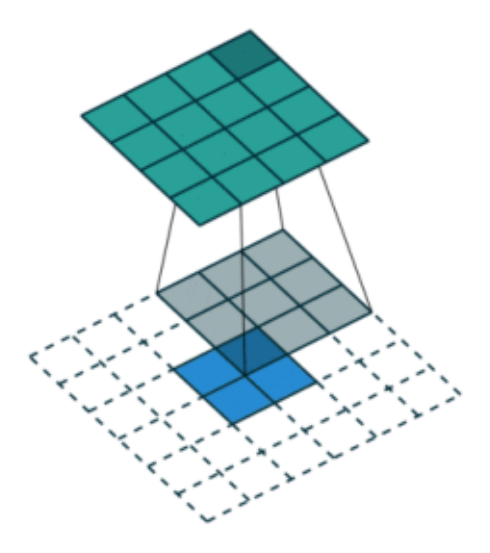
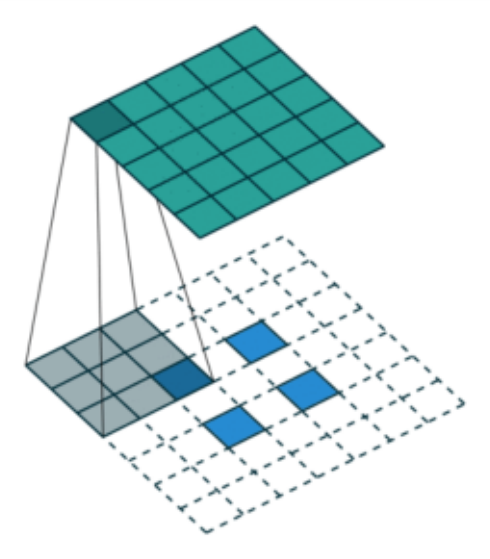


Images from fvisin Francesco

Upsampling using "Transpose Convolution"

Padding = 2, Stride = 1.

Blue - input image, gray - filter, green - output image.

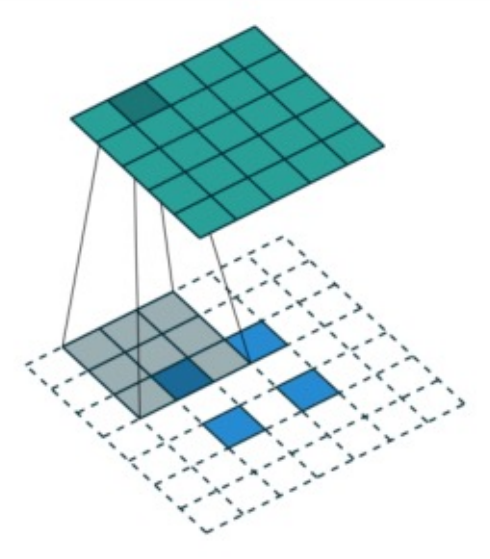


Images from fvisin Francesco

Upsampling using "Transpose Convolution"

Padding = 2, Stride = 1.

Blue - input image, gray - filter, green - output image.



Images from fvisin Francesco

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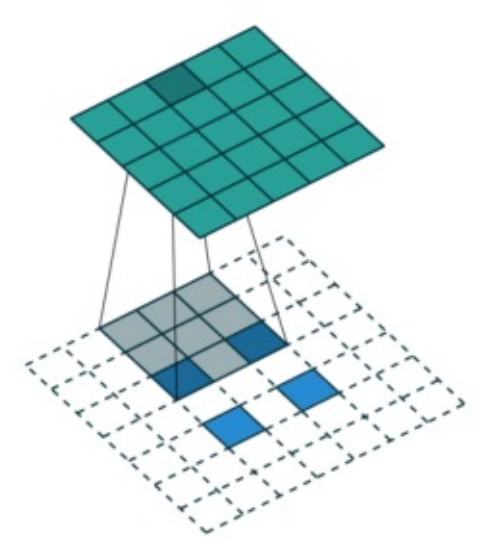
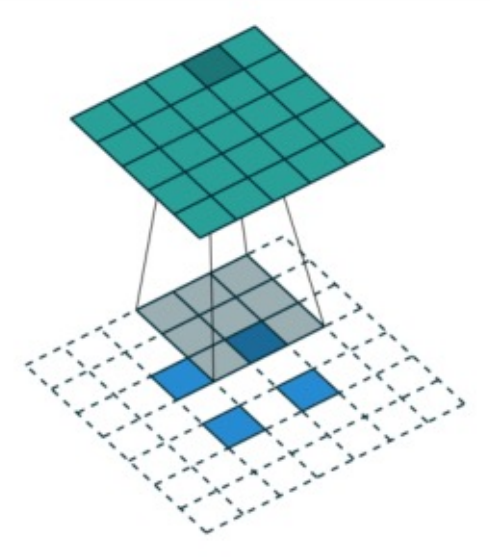


Images from fvisin Francesco

Upsampling using "Transpose Convolution"

Padding = 2, Stride = 1.

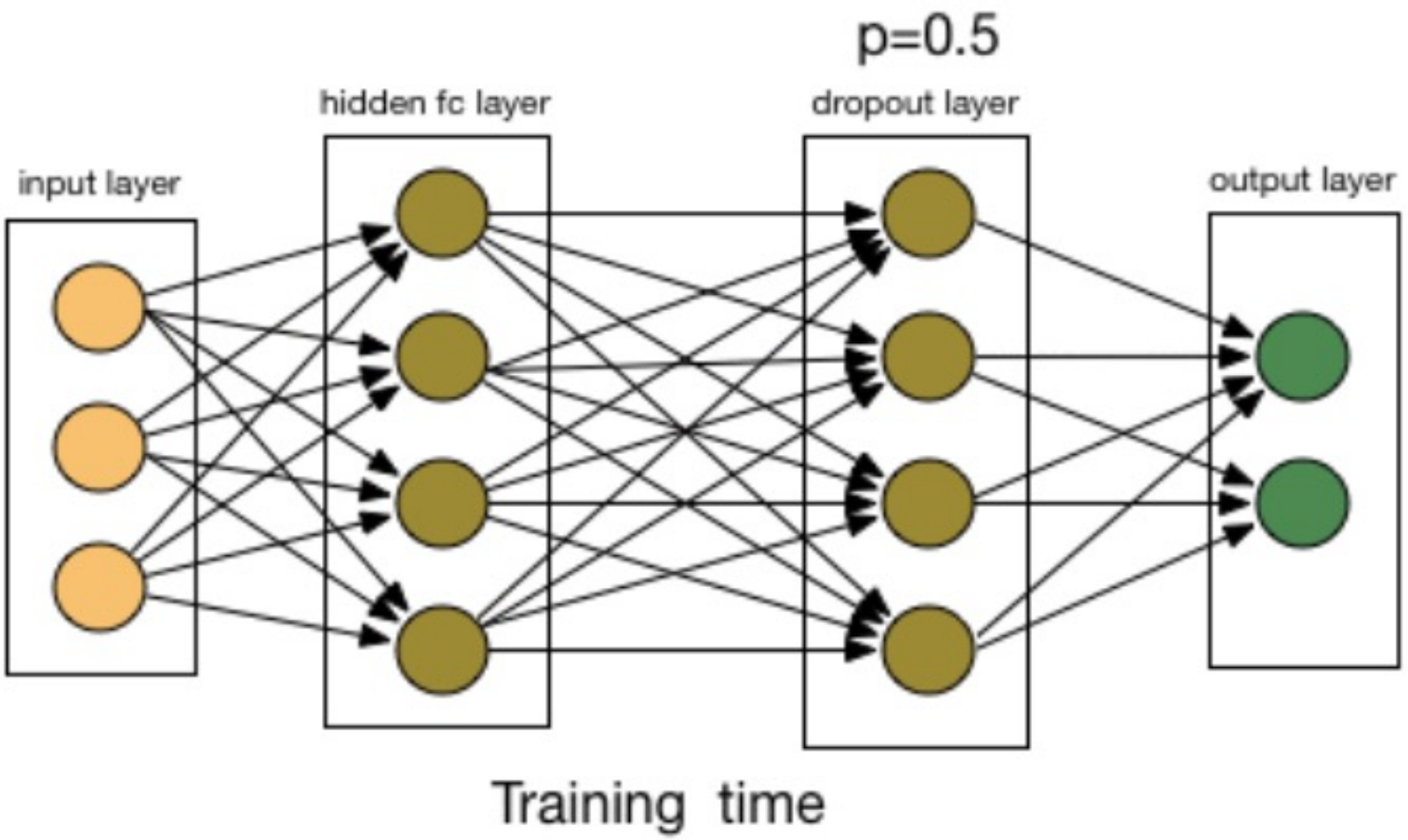
Blue - input image, gray - filter, green - output image.



Images from fvisin Francesco

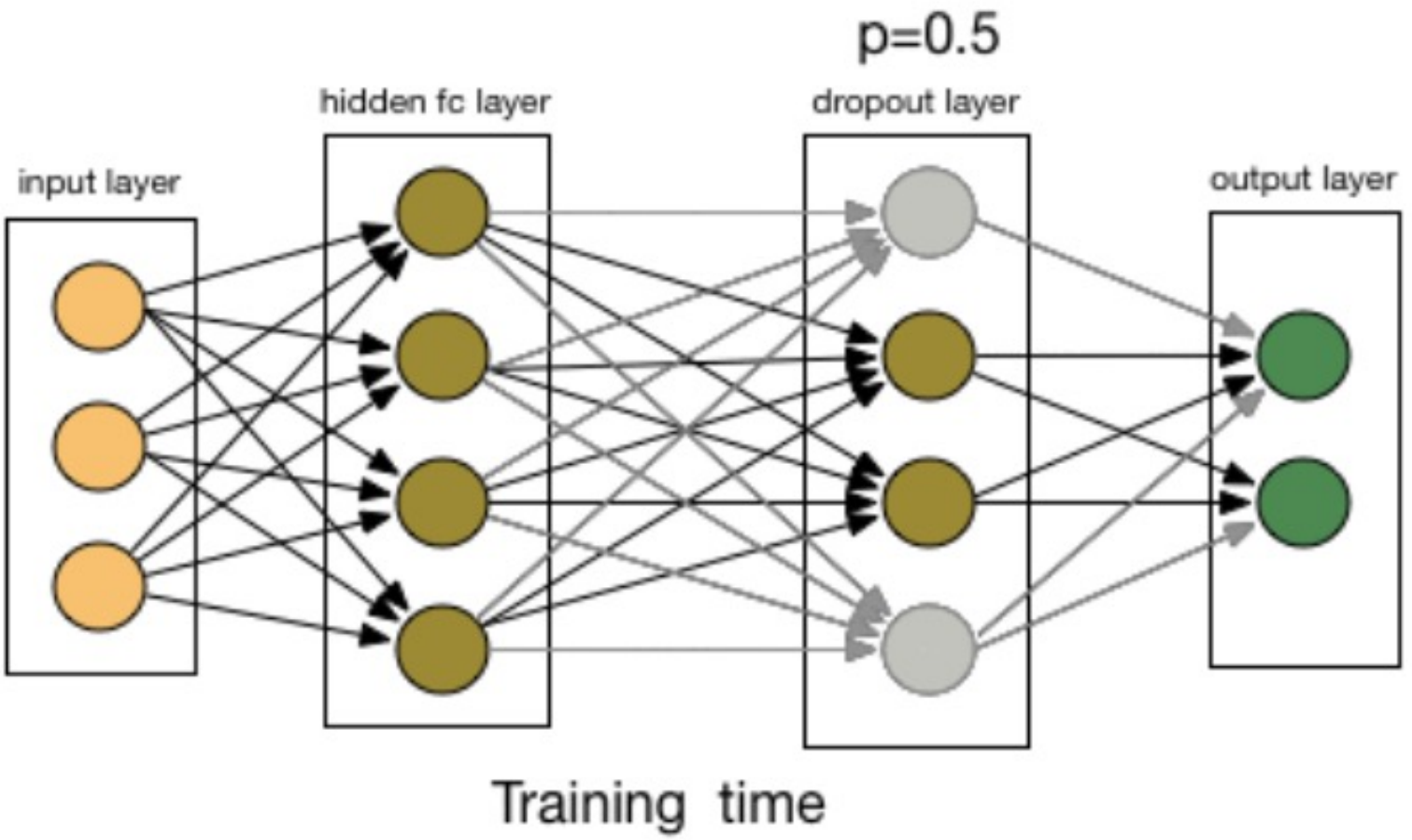
Régularisation : dropout

Utilisation de régularisation Ridge/Lasso pour éviter le surapprentissage.
On a aussi la possible d'appliquer un taux de dropout.



Régularisation : dropout

On désactive une proportion donnée (dropout rate) certains neurones tirés aléatoirement lors de l'apprentissage.



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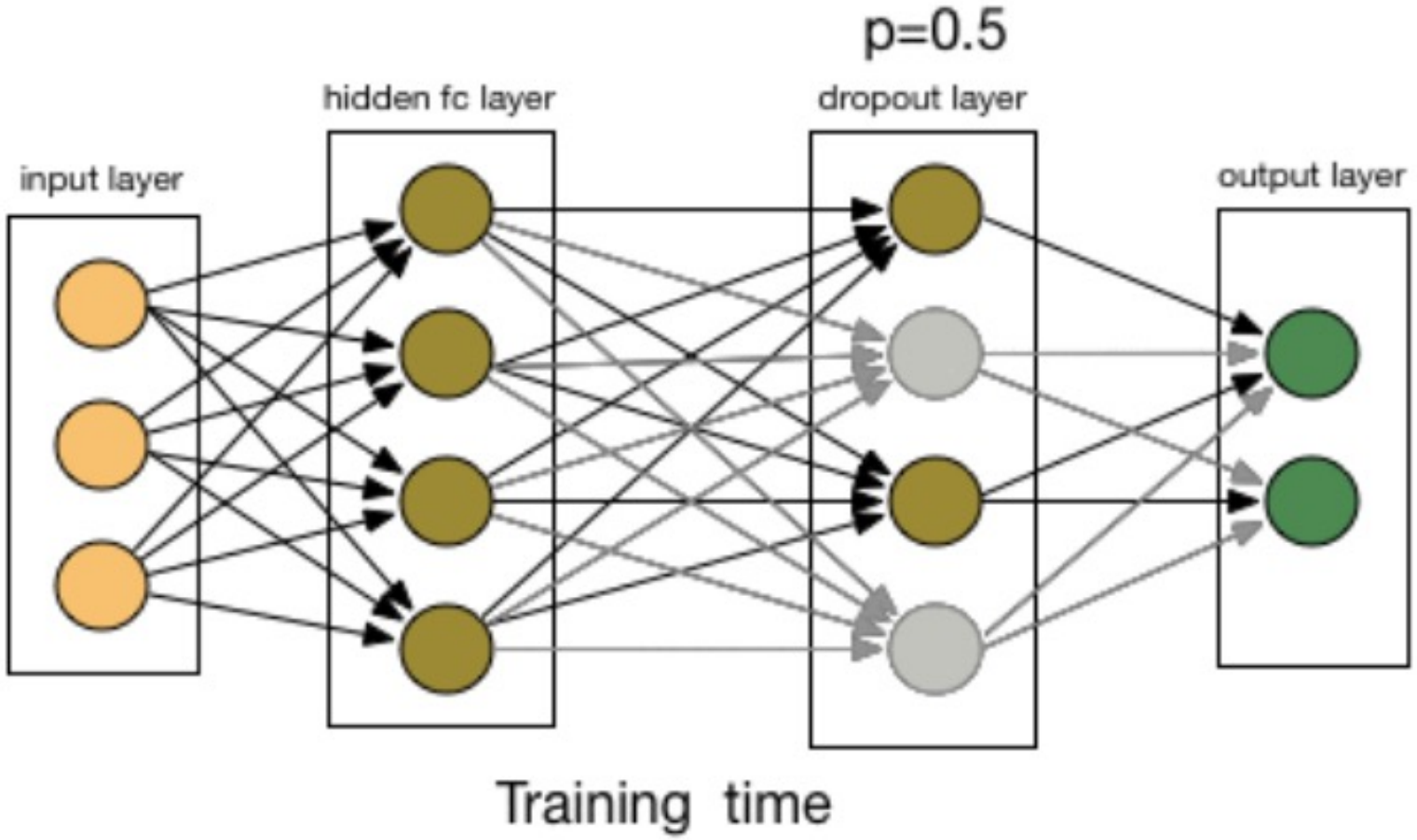
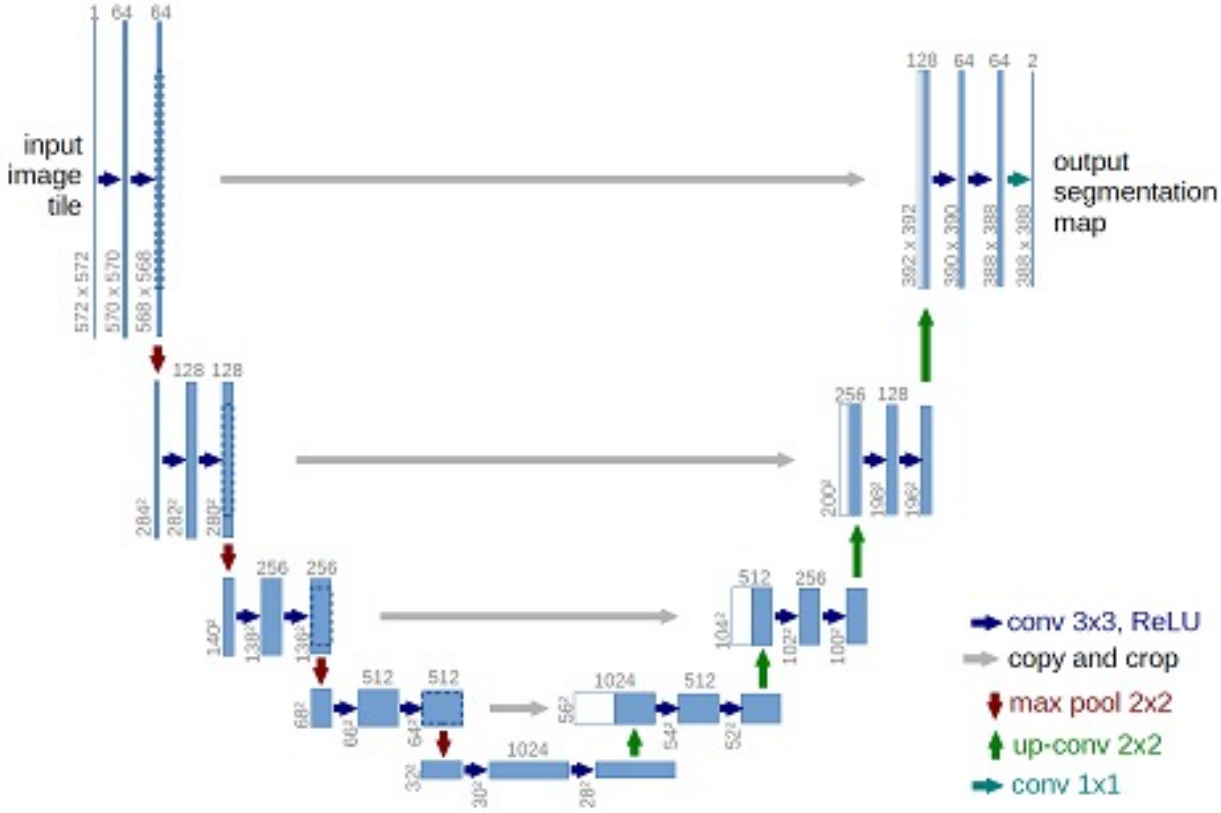


U-Net



Architecture adaptée à l'imagerie médicale très largement adaptée dans d'autre domaines pour la segmentation sémantique.

Ronneberger, O., Fischer, P., & Brox, T. *U-net: Convolutional networks for biomedical image segmentation*. arXiv, 2015. (55K citations)

Travaux pratiques séance 4

Identification des tourbillons océaniques à partir d'une observation de SLA de AVISO.