Analisi di Immagini e Video (Computer Vision)

Giuseppe Manco

Outline

- Reti Neurali
- CNN
- Architetture di rete

Crediti

- Slides adattate da vari corsi e libri
  - Deep Learning (Ettore Ritacco)
  - Deep Learning (Bengio, Courville, Goodfellow, 2017)
  - Andrey Karpathy
  - Computer Vision (I. Gkioulekas) - CS CMU Edu
  - Cmputational Visual Recognition (V. Ordonez), CS Virgina Edu

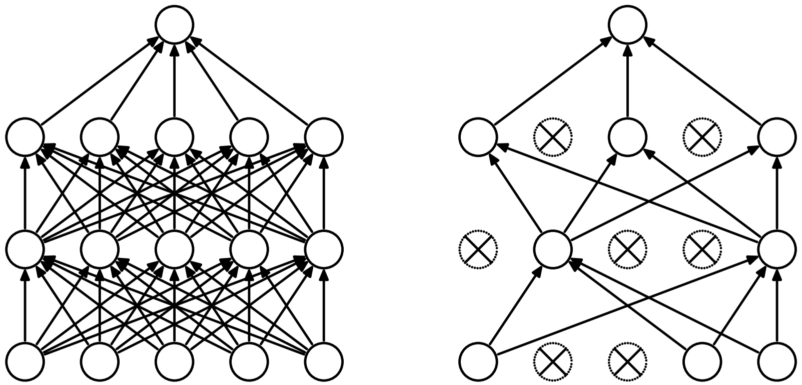
Concetti avanzati

Deep learning effettivo

- Regolarizzazione
  - Aggiunge una penalizzazione sui pesi nella funzione di loss
  - Criteri: sparsità, norma, …
- Dropout
  - Reset di un numero random di pesi
  - Decorrela i nodi nella rete
- Gradient clipping
  - Gradient exploding
- Smart initialization
  - Better random initialization methods (Glorot and Bengio, 2010)
- Data augmentation
  - More to come later…

Dropout

- Rimozione random di nodi durante il forward pass nel training



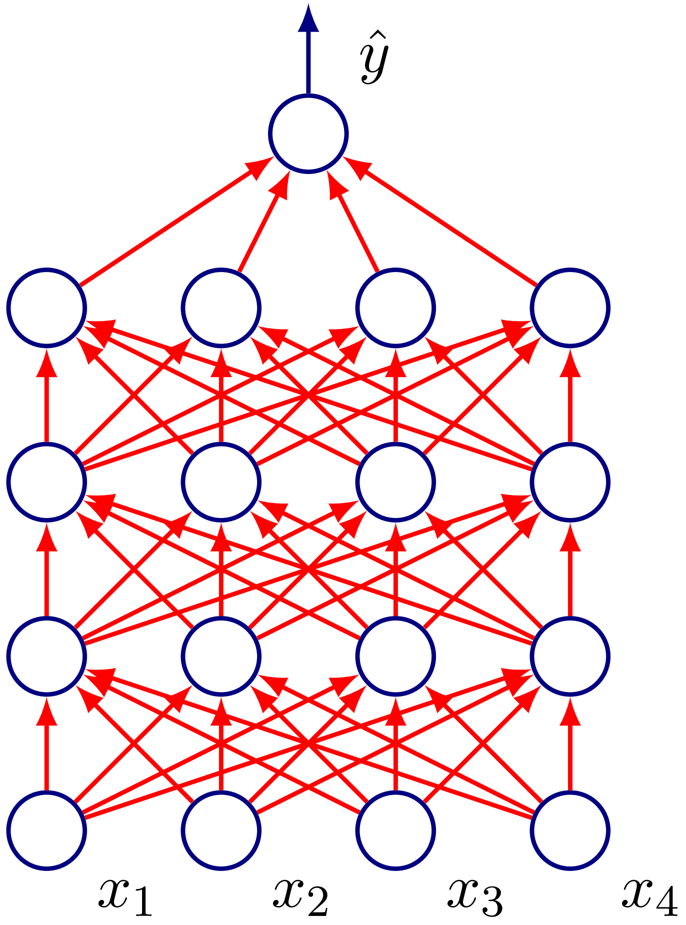
(a) Standard Neural Net (b) After applying dropout.

Dropout

- Aumenta l’indipendenza delle unità
  - Co-adaptation
    - Una unità interna non può basarsi su altre unità
- Interpretazione in termini di ensembles

Convoluzione

Fully connected networks



$$a_i = \sum_{j \prec i} w_{i,j} z_j$$

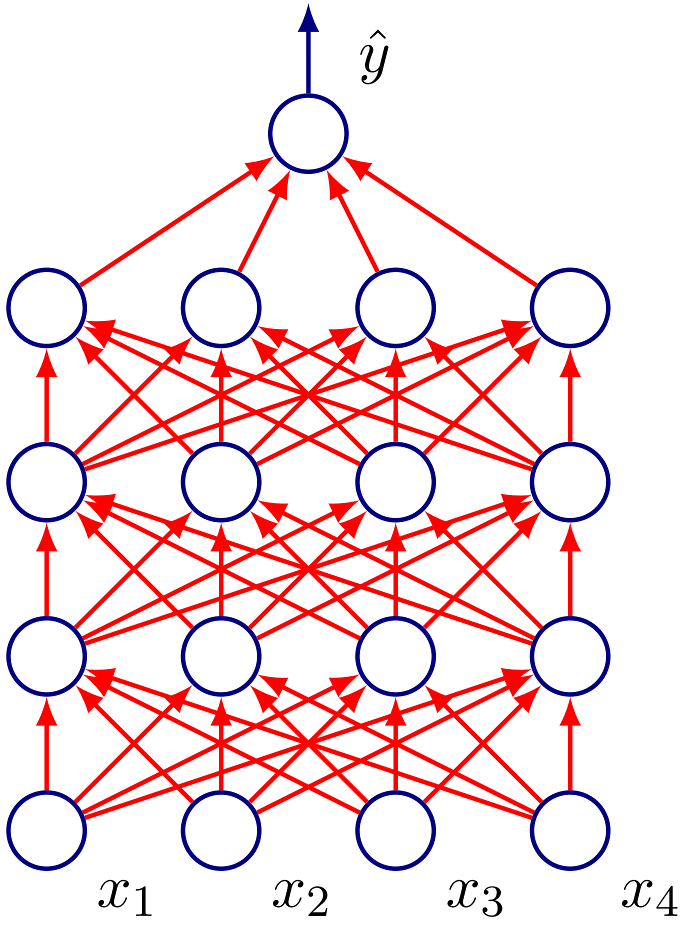
$$z_i = f(a_i)$$

$$\mathbf{a}^{(h+1)} = \mathbf{W}^{(h)} \mathbf{z}^{(h)}$$

$$\mathbf{z}^{(h+1)} = f\left(\mathbf{a}^{(h+1)}\right)$$

$$\mathbf{z}^{(0)} = \mathbf{x}$$

Fully connected networks



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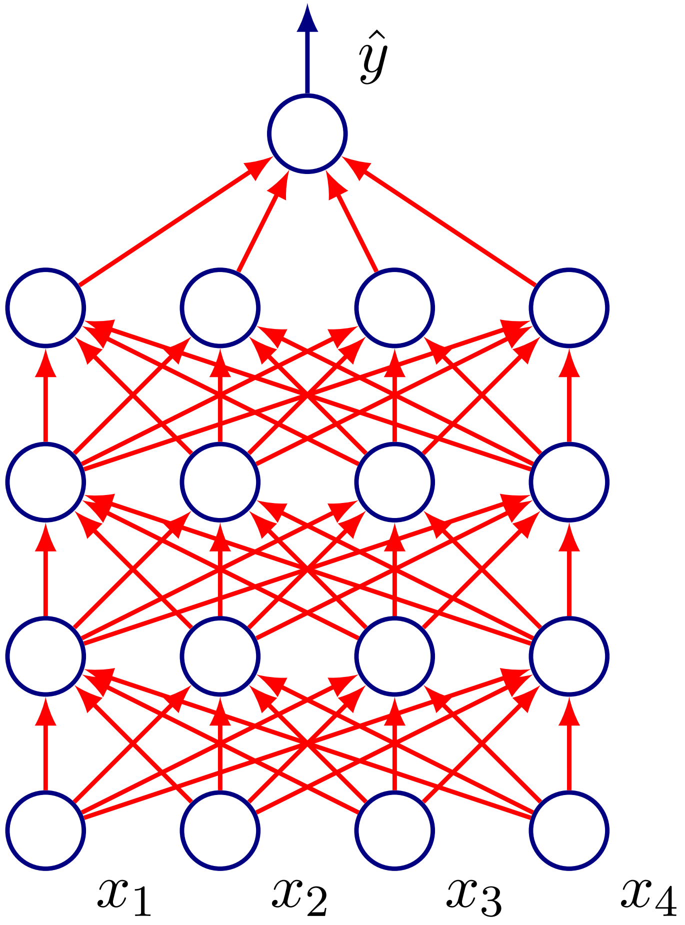
- Ogni elemento connesso agli altri
  - (5*4) + (5*4) + (5*4) + 5 connections

Fully connected networks



Quanti sono i parametri di una generica rete?

$$a_i = \sum_{j \prec i} w_{i,j} z_j$$

$$z_i = f(a_i)$$

$$\mathbf{a}^{(h+1)} = \mathbf{W}^{(h)} \mathbf{z}^{(h)}$$

$$\mathbf{z}^{(h+1)} = f\left(\mathbf{a}^{(h+1)}\right)$$

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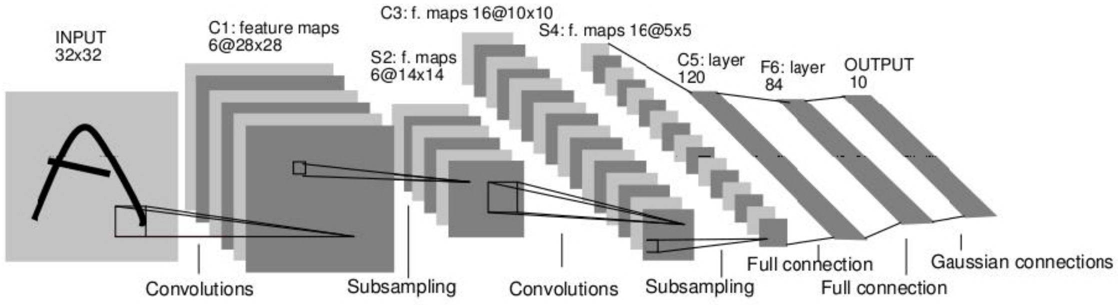
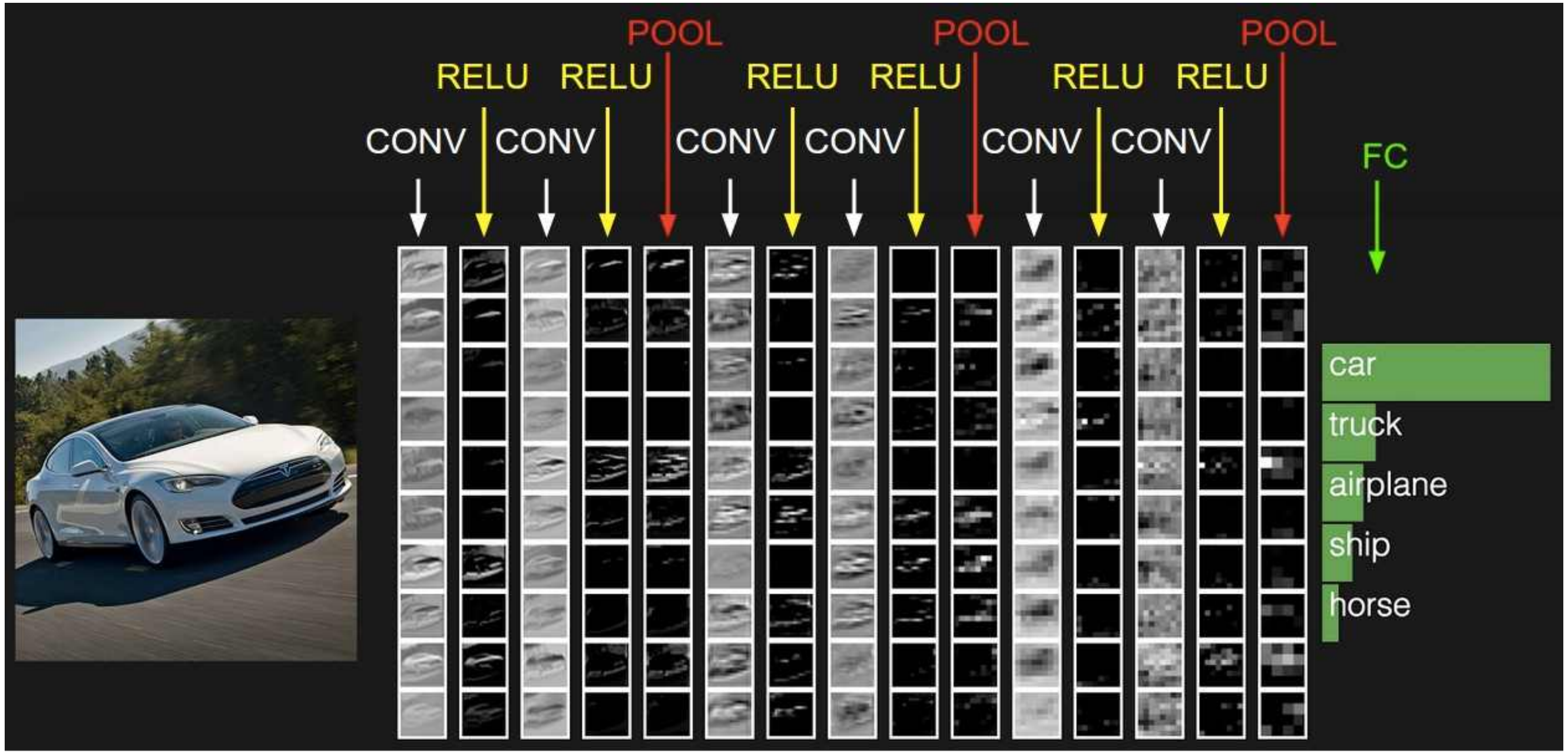
Convolutional networks

- Reti neurali che usano la convoluzione

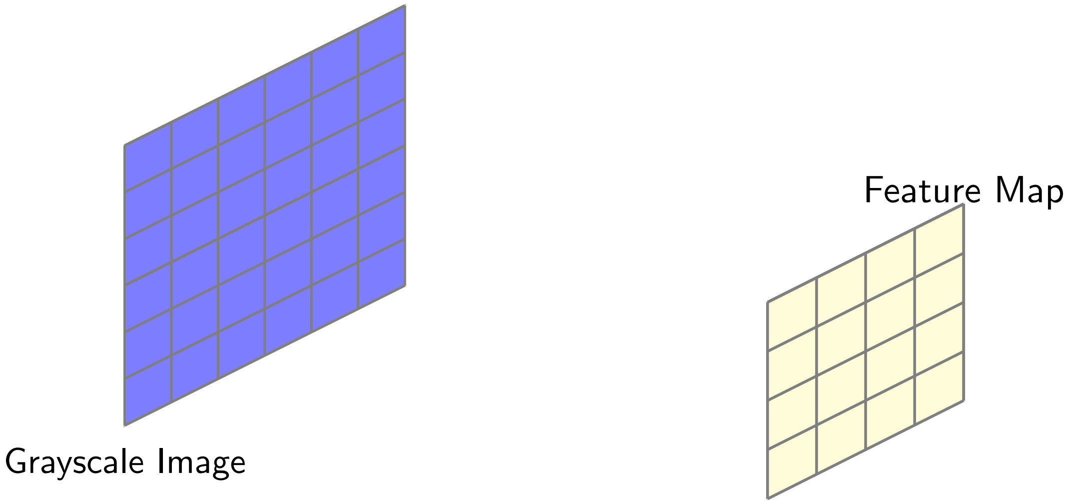


  - Convolution
  - pooling

Convolutional neural networks

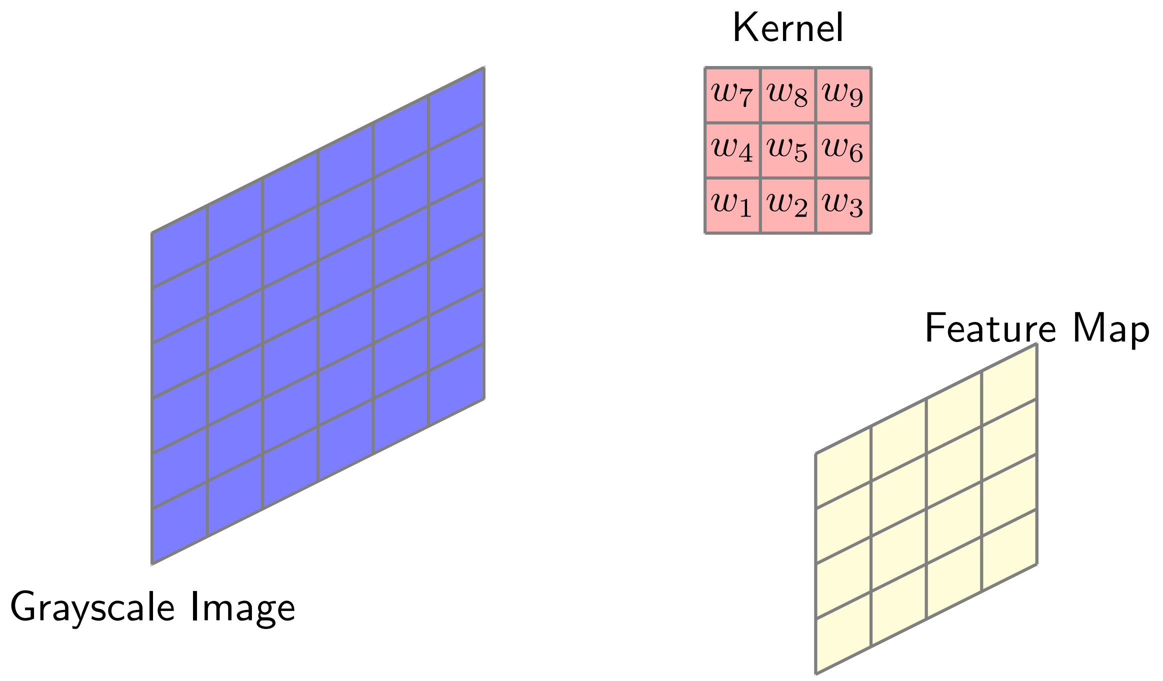


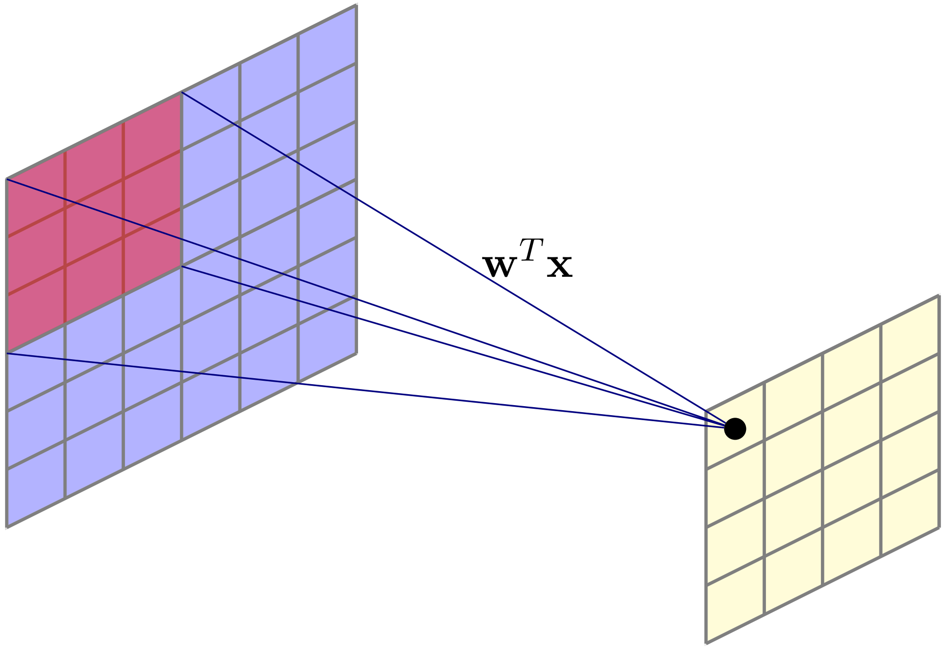
Convolution

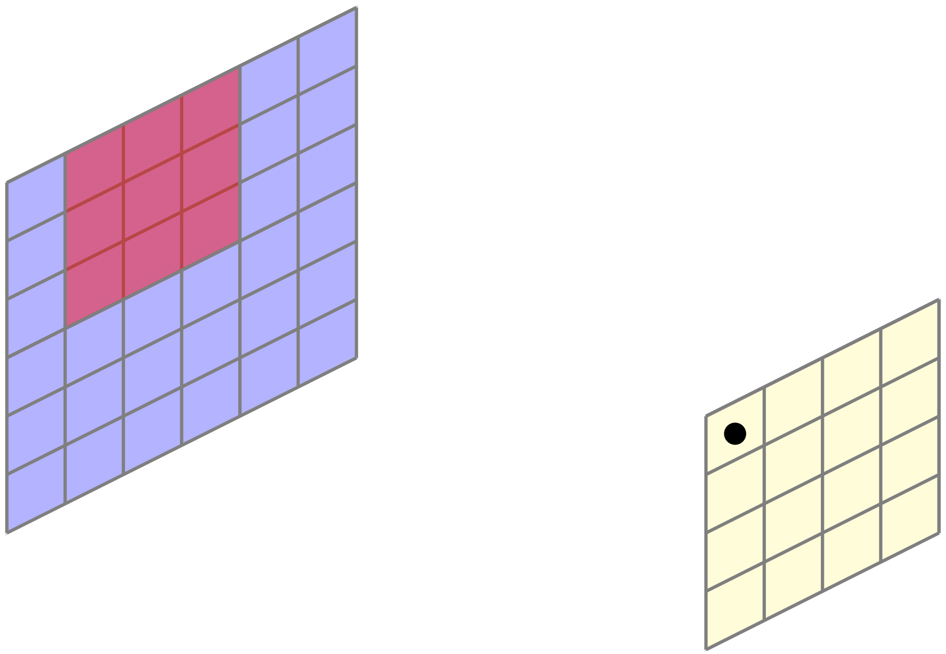


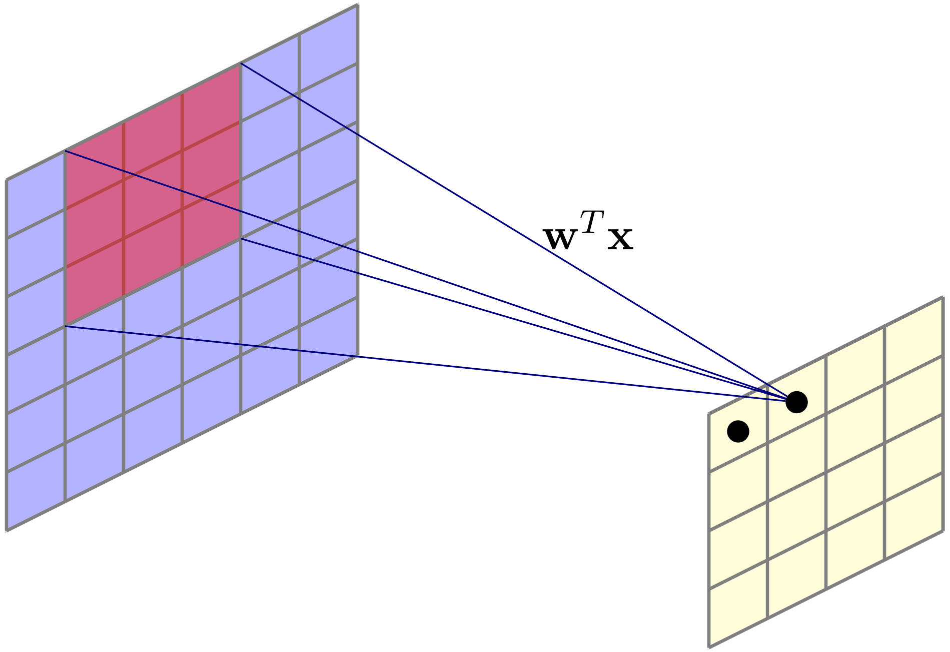
- Qual è il numero di parametri?

Convolution




$\mathbf{w}^T\mathbf{x}$

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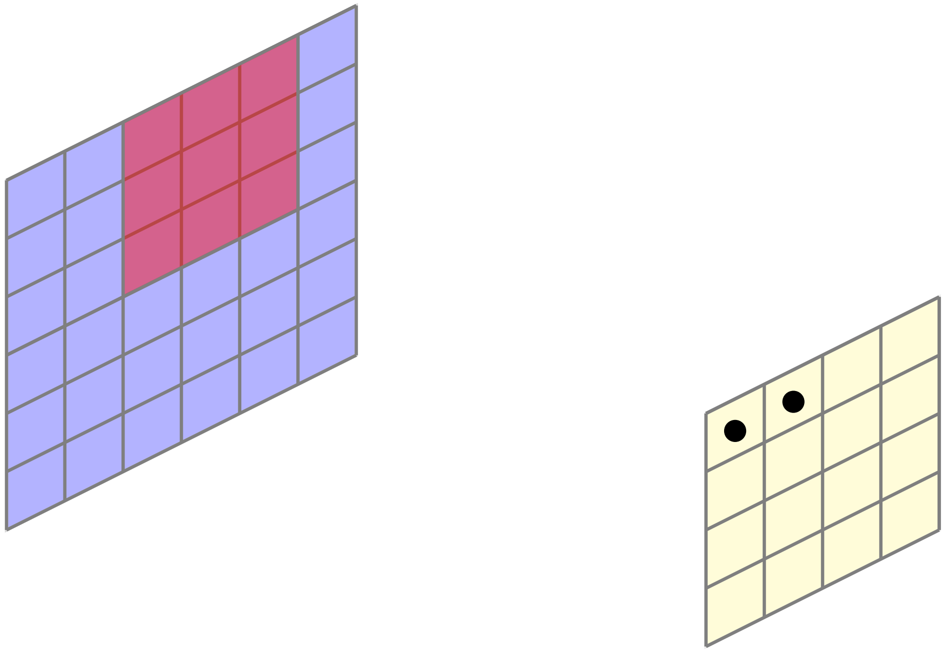

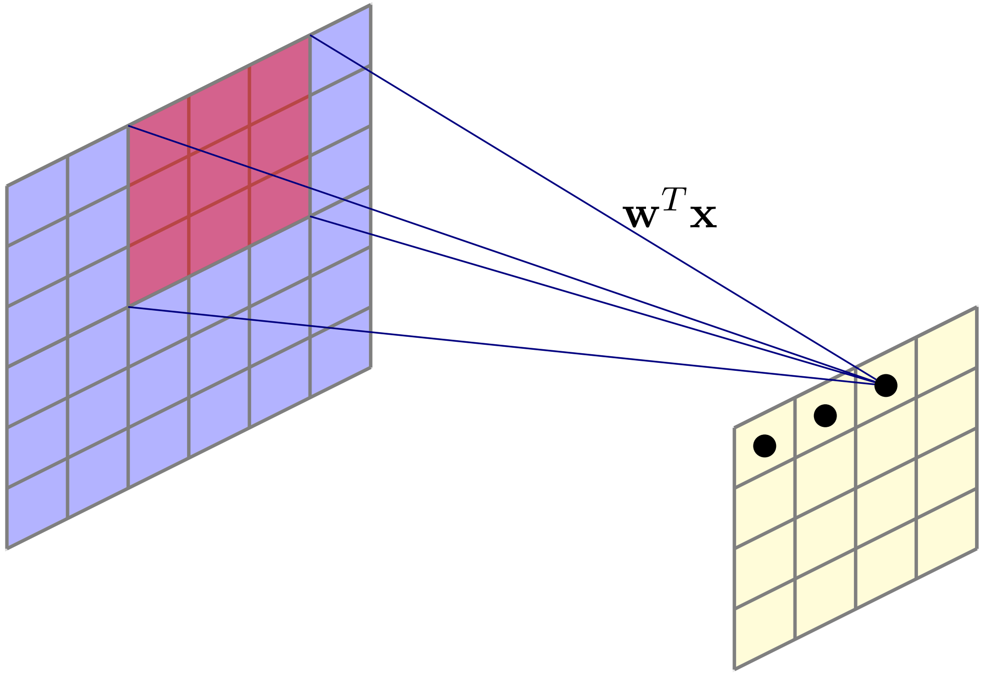
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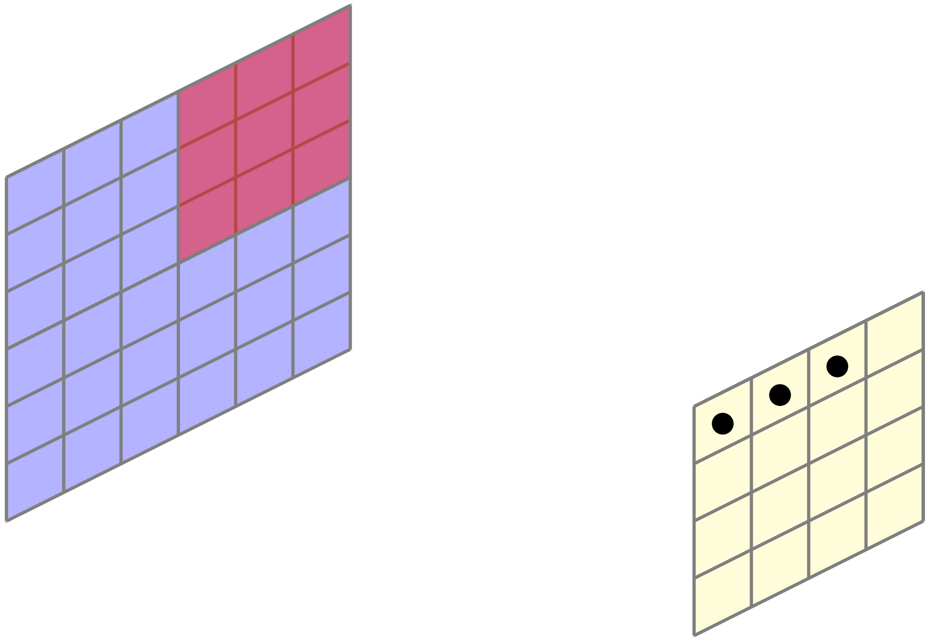

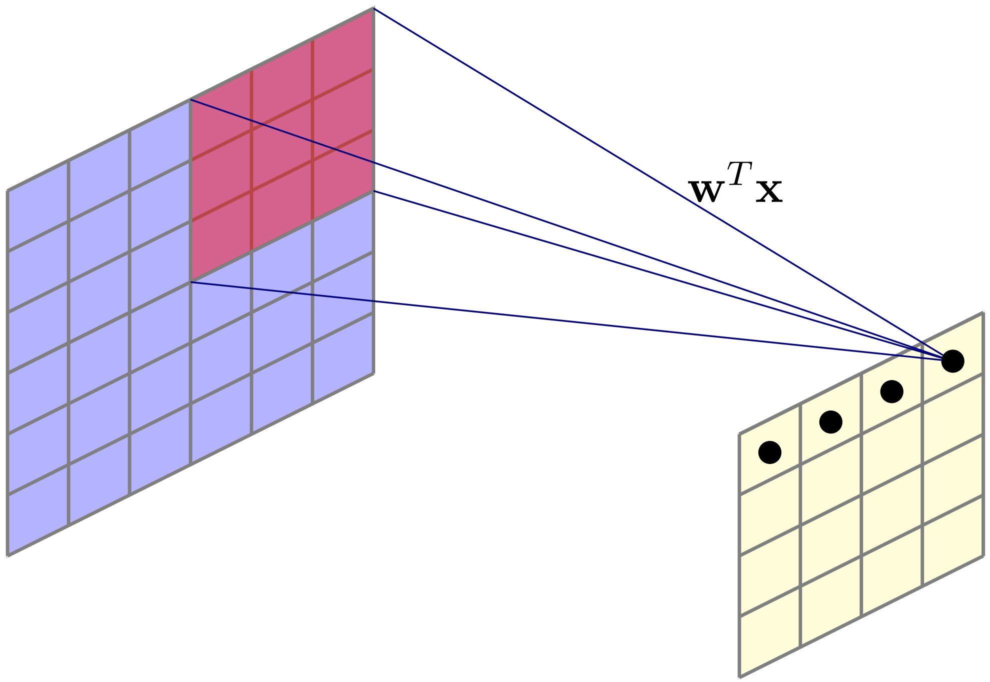
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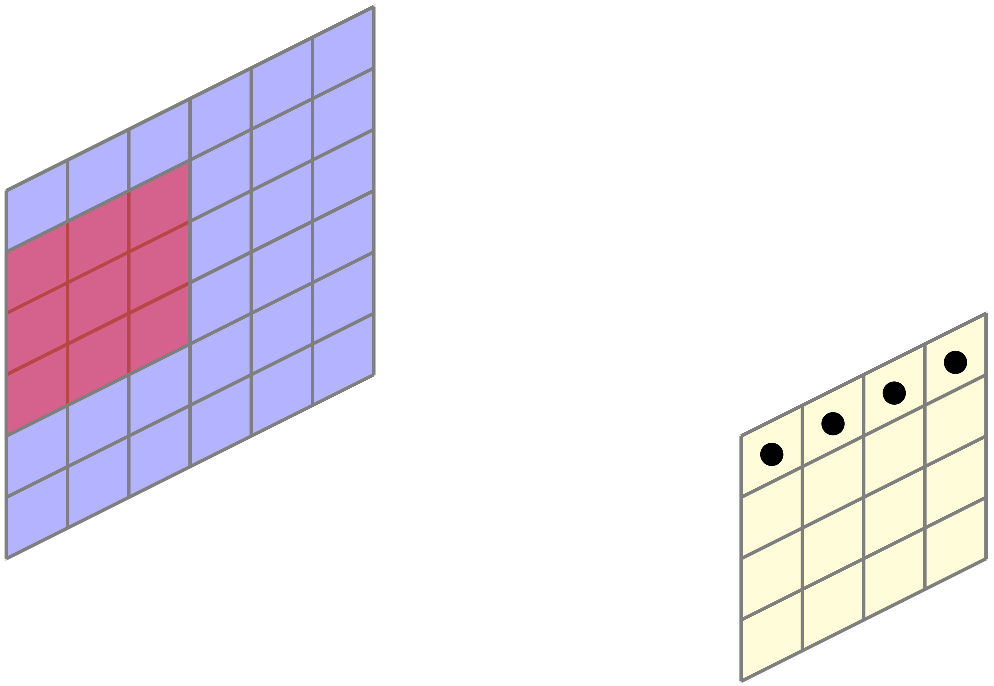

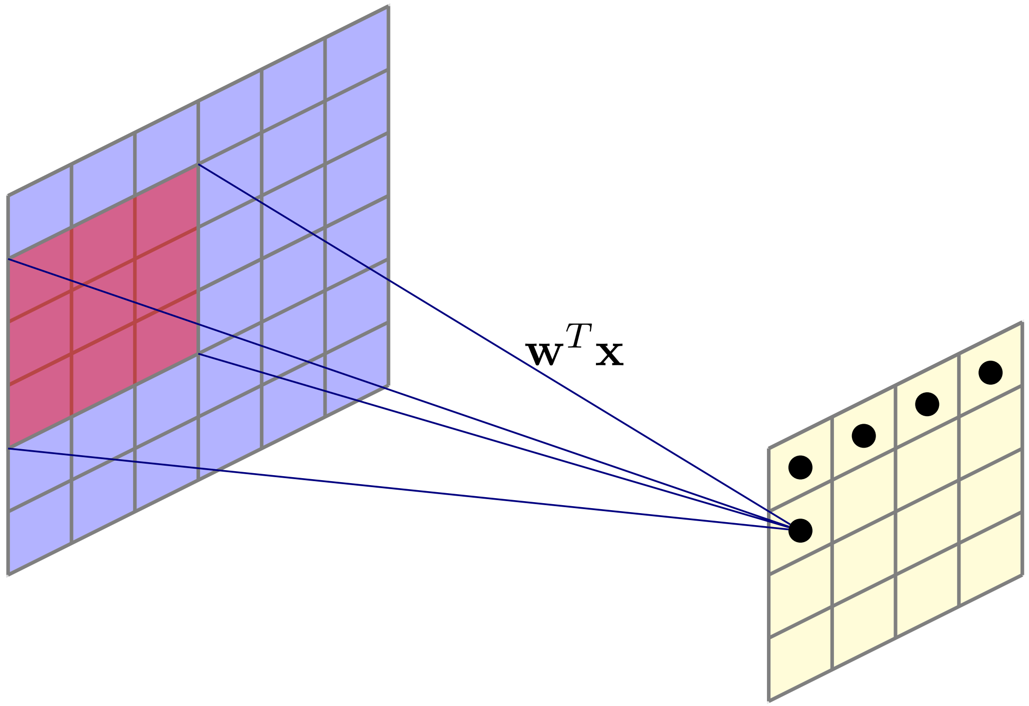
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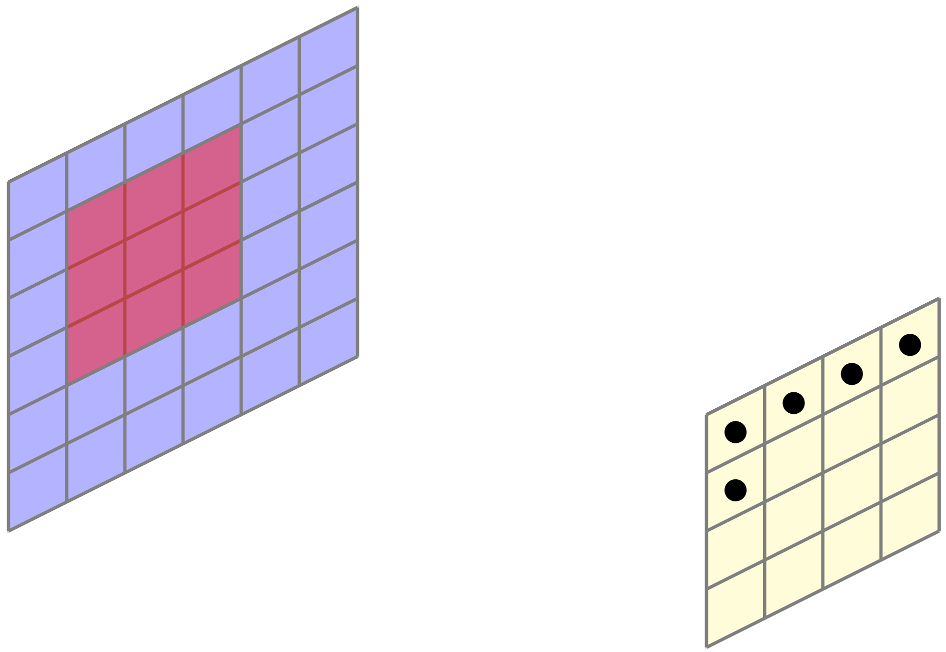

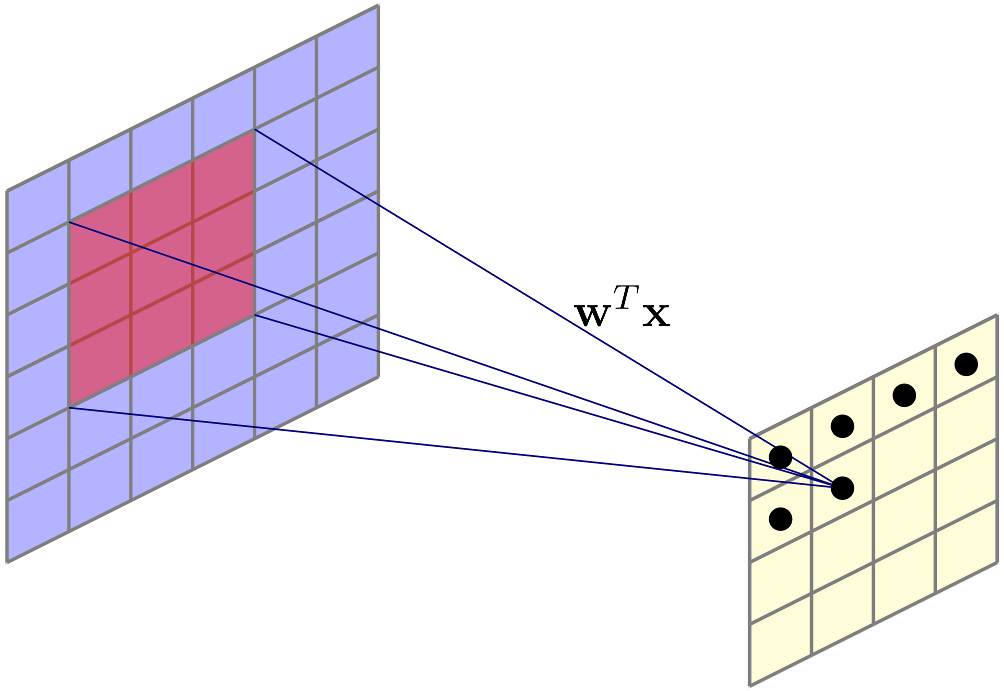
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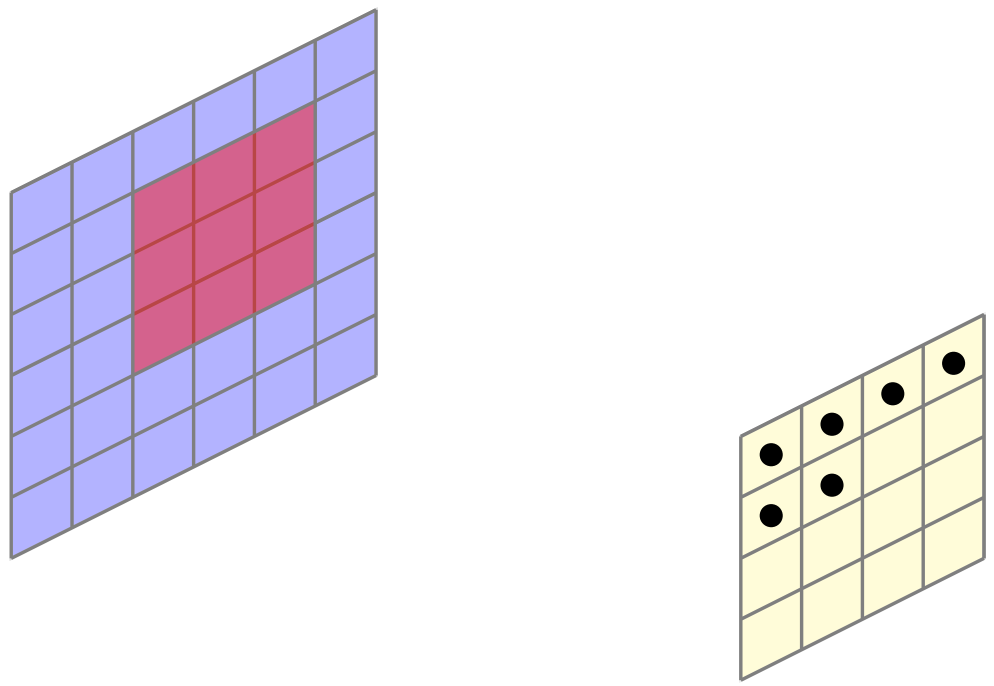

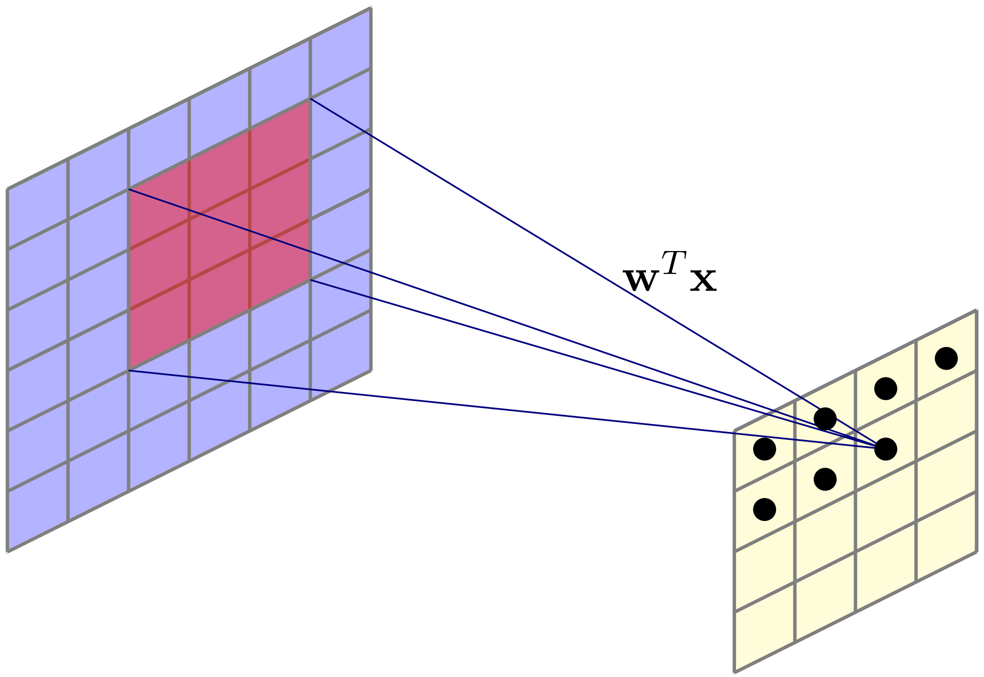
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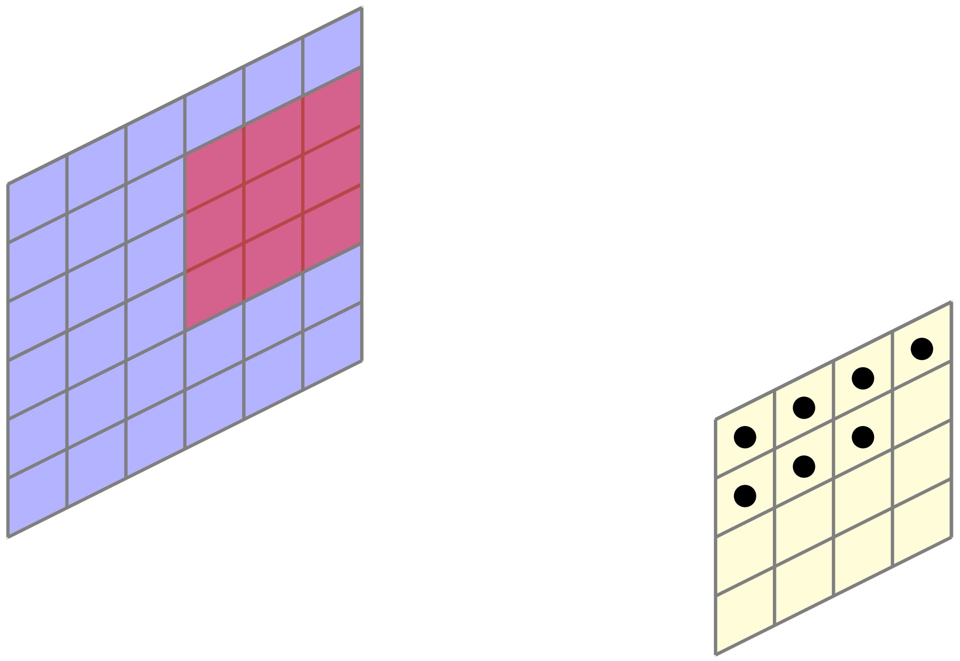

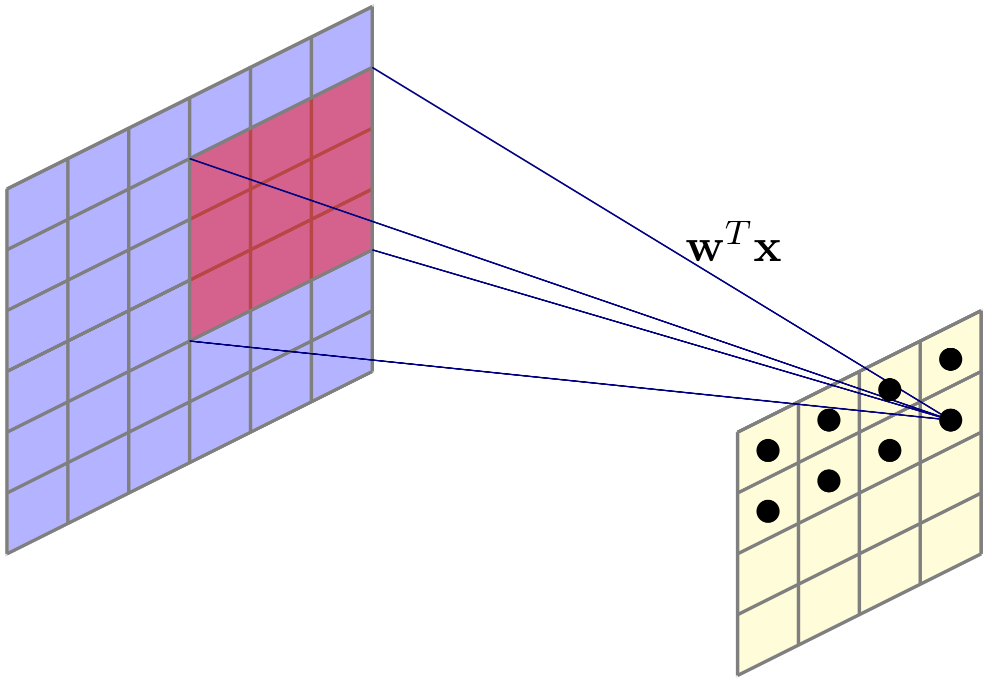
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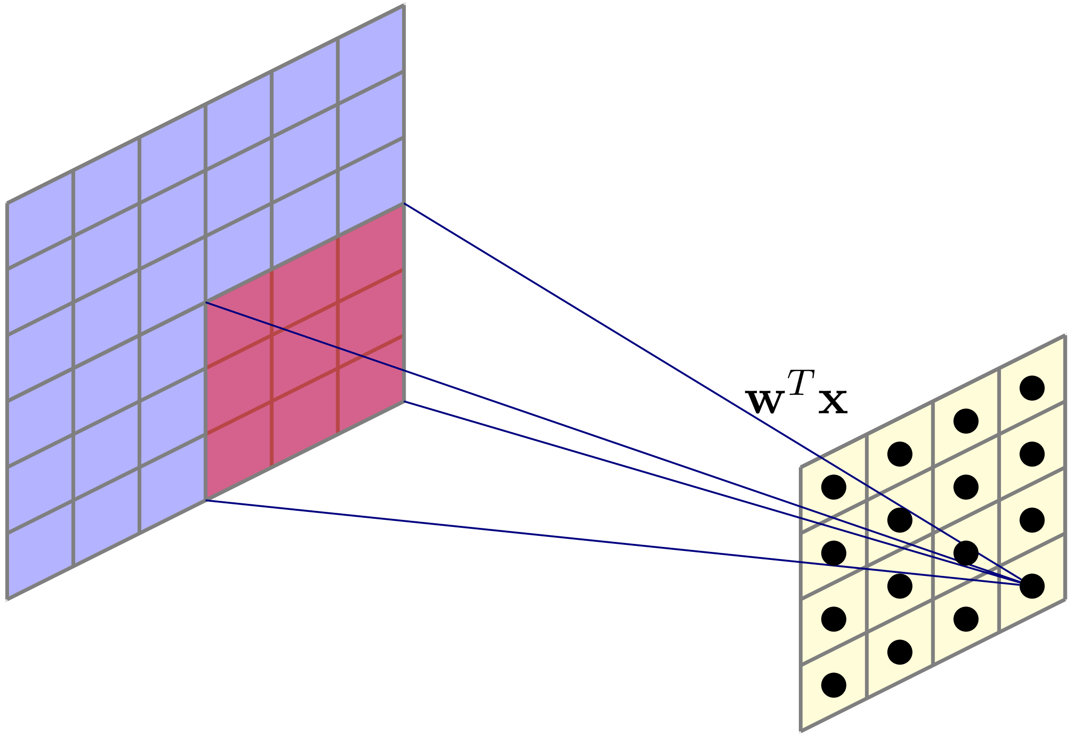
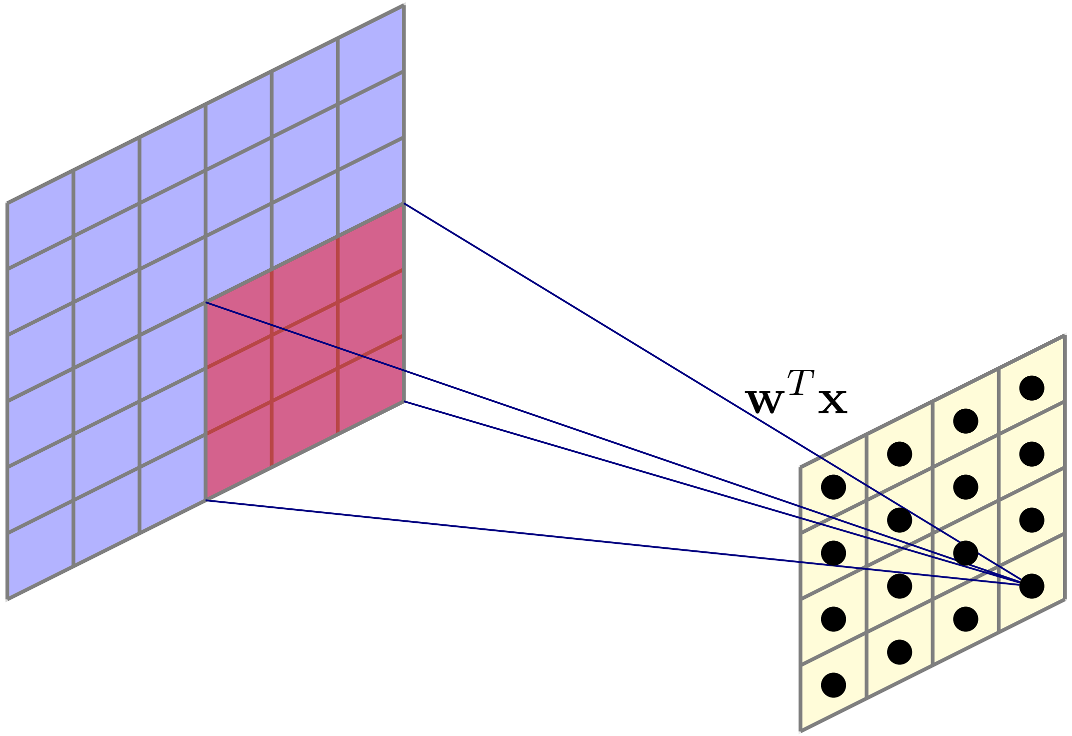

$\mathbf{w}^T\mathbf{x}$

Convolution

- Qual è il numero di parametri?



Convoluzione

$$a_{j,k}^{(h)} = \sum_{l=1}^{c} \sum_{m=1}^{d} w_{m,l} z_{j+l,k+m}^{(h-1)}$$

- I pesi rappresentano il kernel di dimensione (c,d)
- Condivisione!

Padding, strides, dilation

- https://github.com/vdumoulin/conv_arithmetic

Output

- Stride
  - S=1
- Kernel with receptive field
  - K=3
- No padding
- Output size

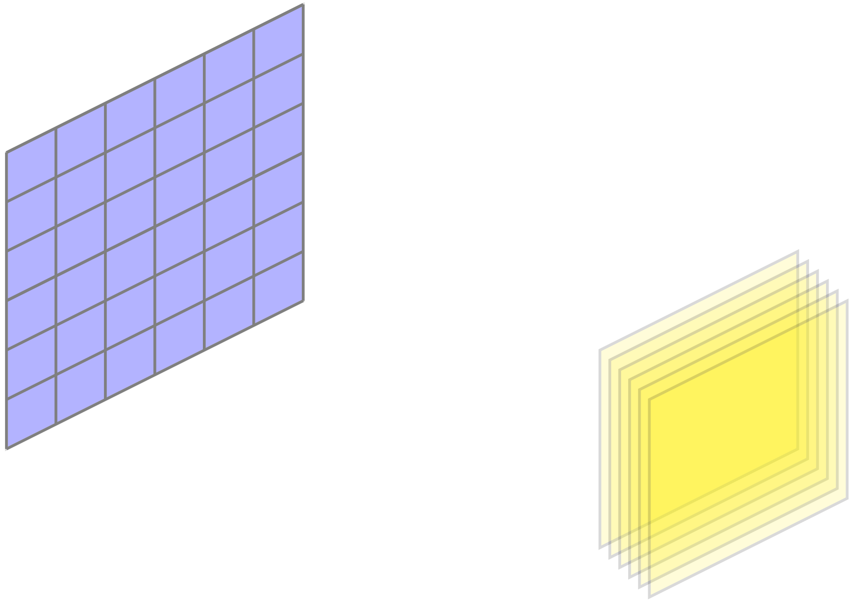
  - 4

Output, revisited

- Input I
- Padding P
- Kernel size K
- Stride S
- Dilation D
- Output size:

$$\left\lfloor \frac{I - K - (K-1)(D-1) + 2P}{S} \right\rfloor + 1$$

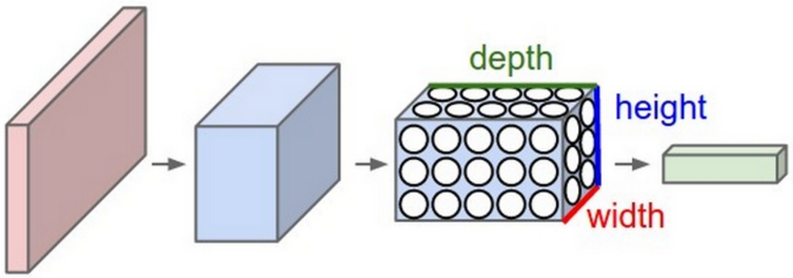
Multiple filters



- Ogni feature map idenfiticata da un kernel
  - In total, il numero dei pesi è dato dal numero di kernel per la size della feature map

Volumetrics

- Non solo immagini 2D
  - Volumi
    - Ad esempio, immagini RGB hanno profondità 3



  - Quanti pesi?

Volumetrics

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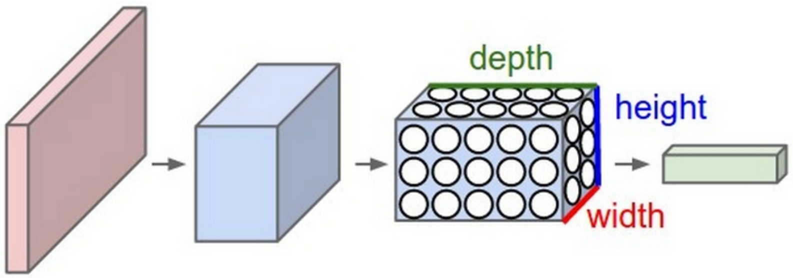
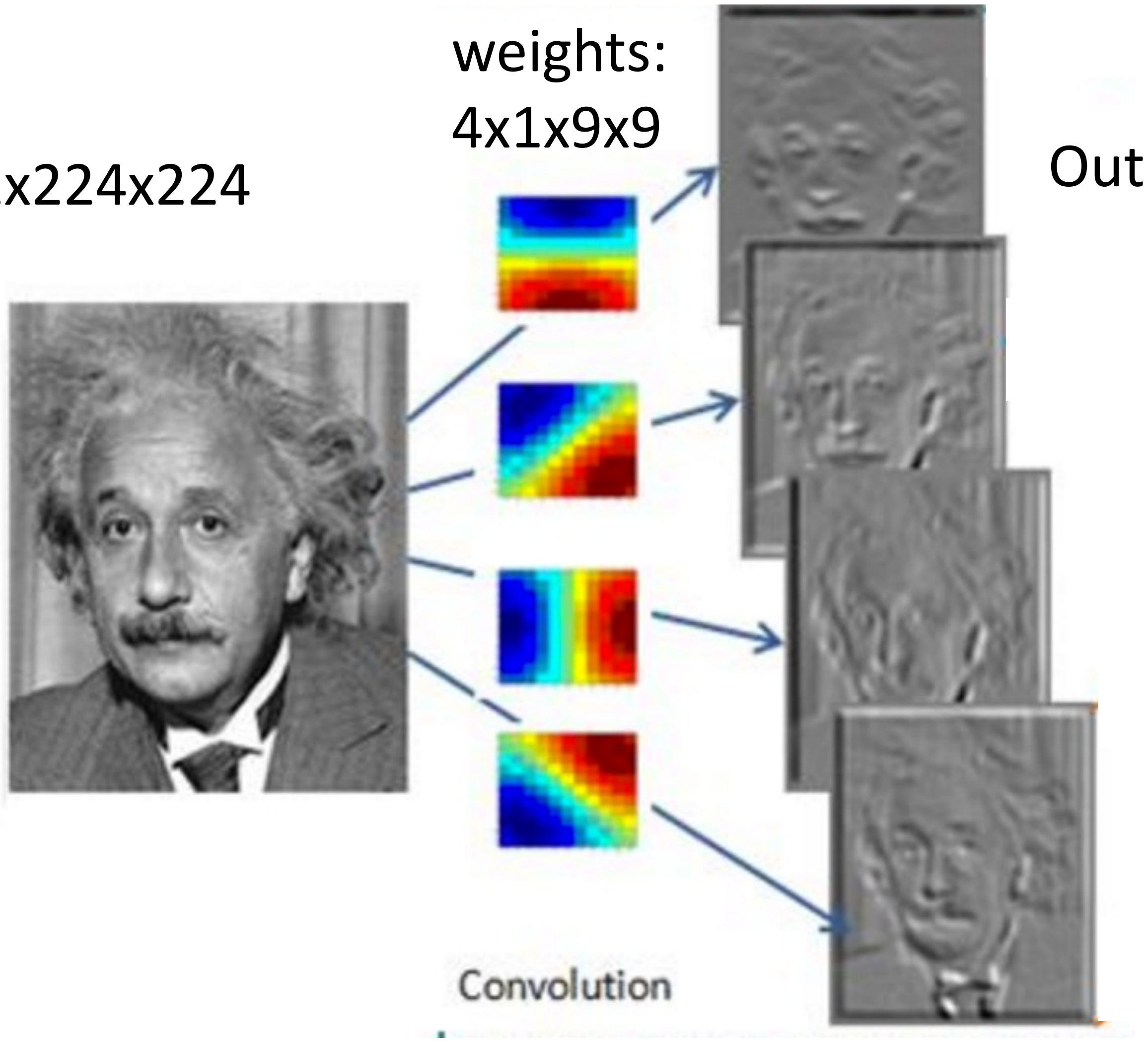


  - Quanti pesi?
    - $a_{i,j}^{f} = \sum_c \sum_{l,p} w_{l,p}^{c,f} \cdot x_{i-l,j-p}^{c} + b^{c,f}$

Convolutional Layer (con 4 filtri)

Input: 1x224x224

weights:
4x1x9x9



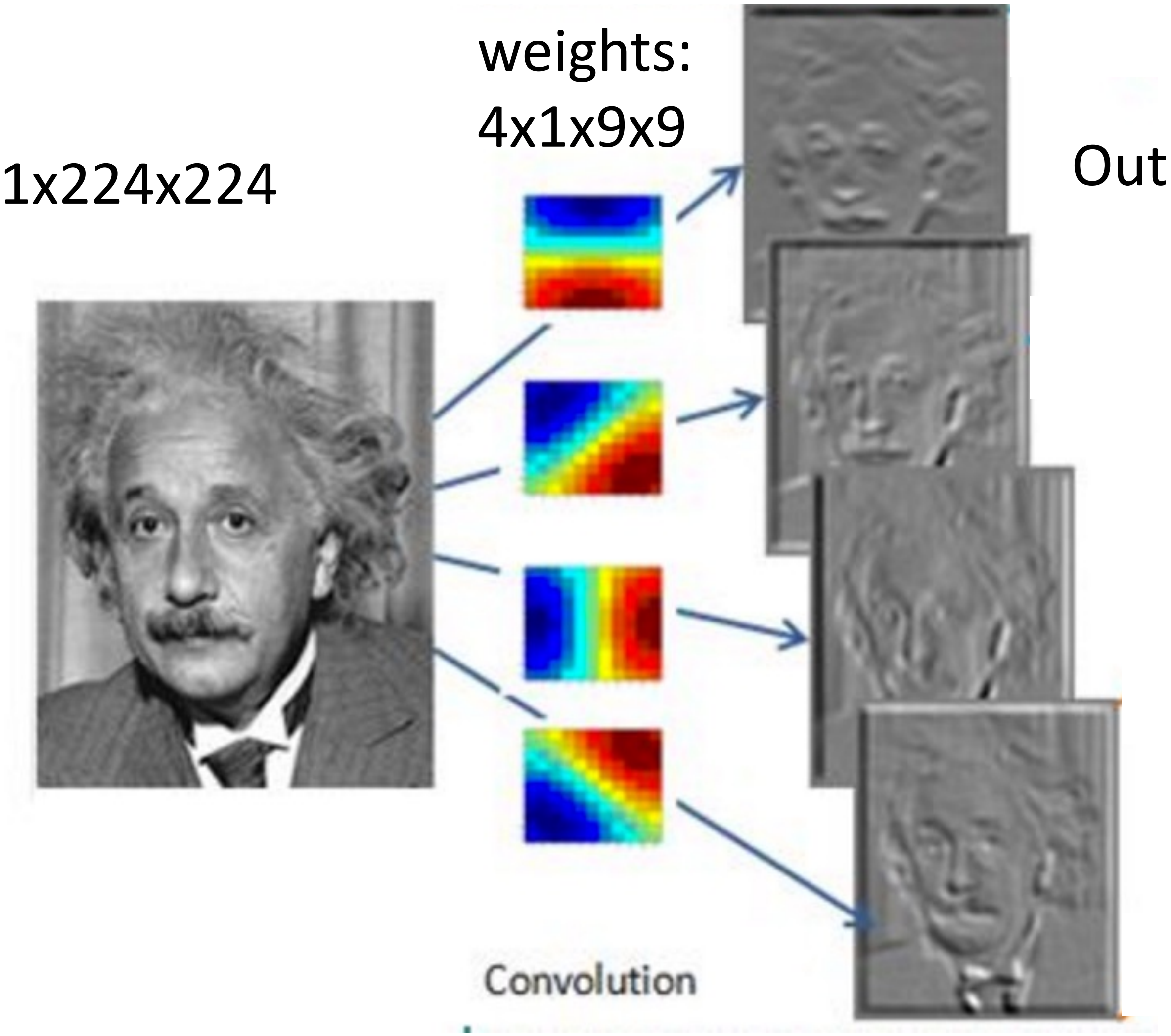
Output: 4x224x224

zero padding,
stride = 1

Convolutional Layer (con 4 filtri)

Input: 1x224x224

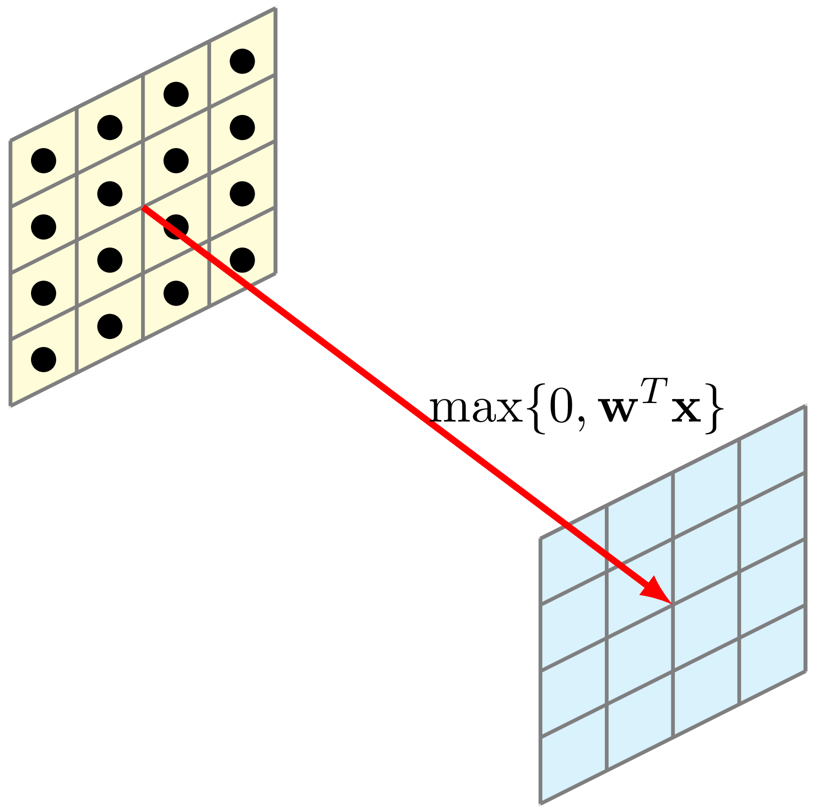
weights:
4x1x9x9



Output: 4x112x112

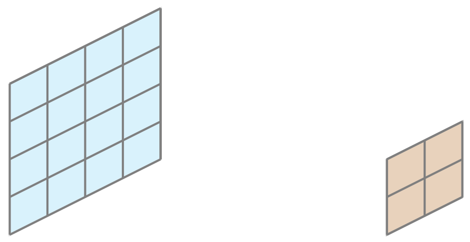
zero padding,
stride = 2

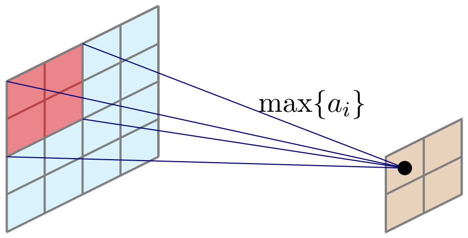
Activation Layer



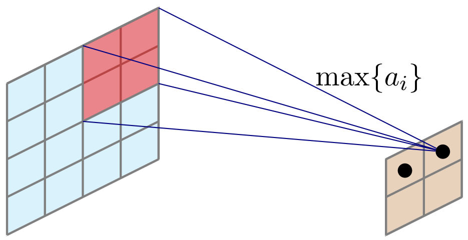
- ReLU

Pooling





$\max\{a_i\}$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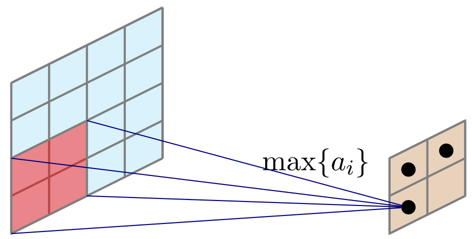
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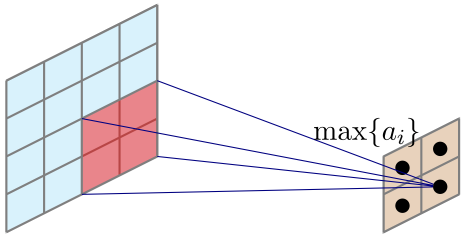
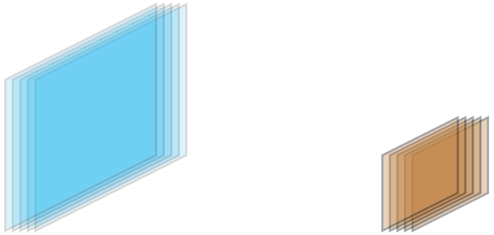
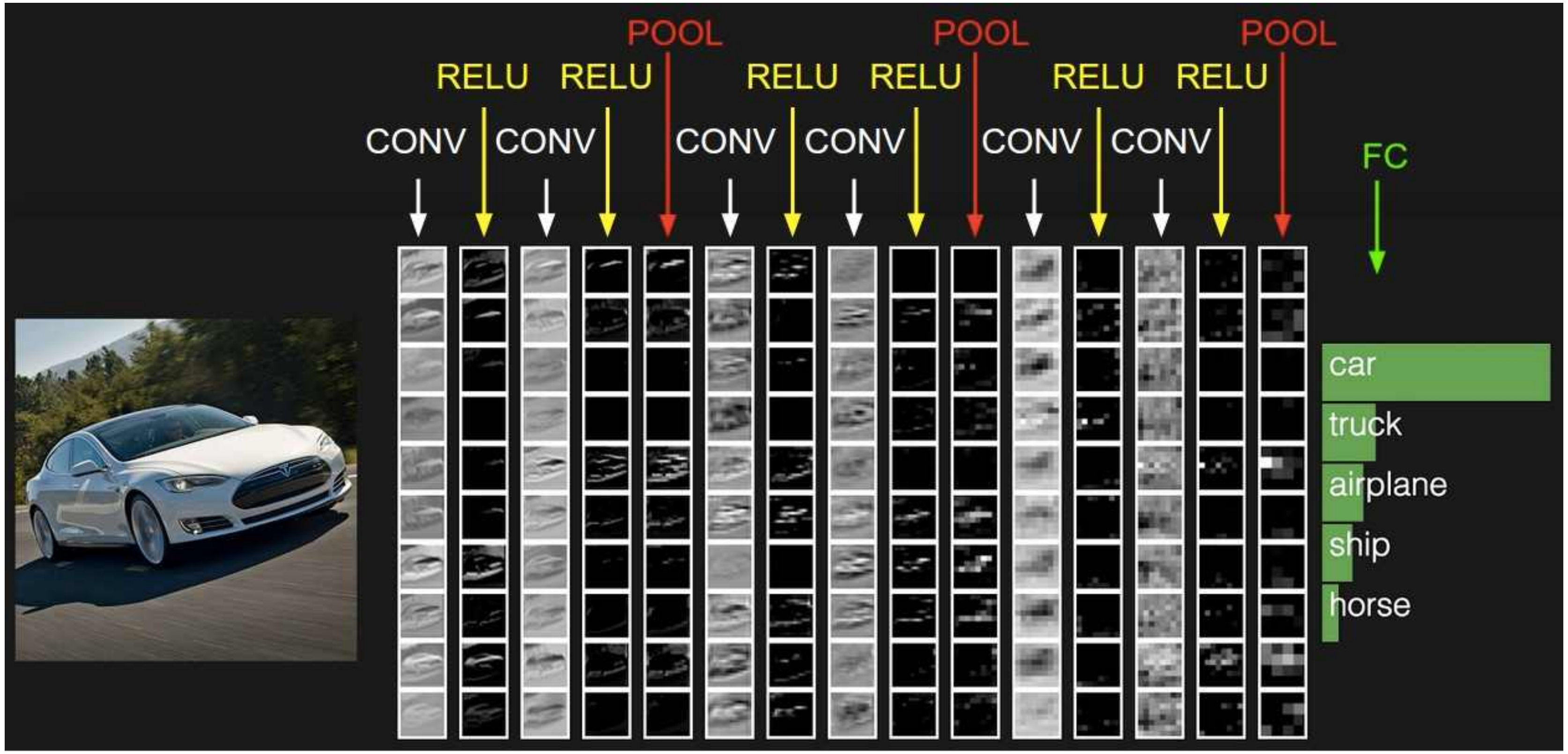

$\max\{a_i\}$

Pooling



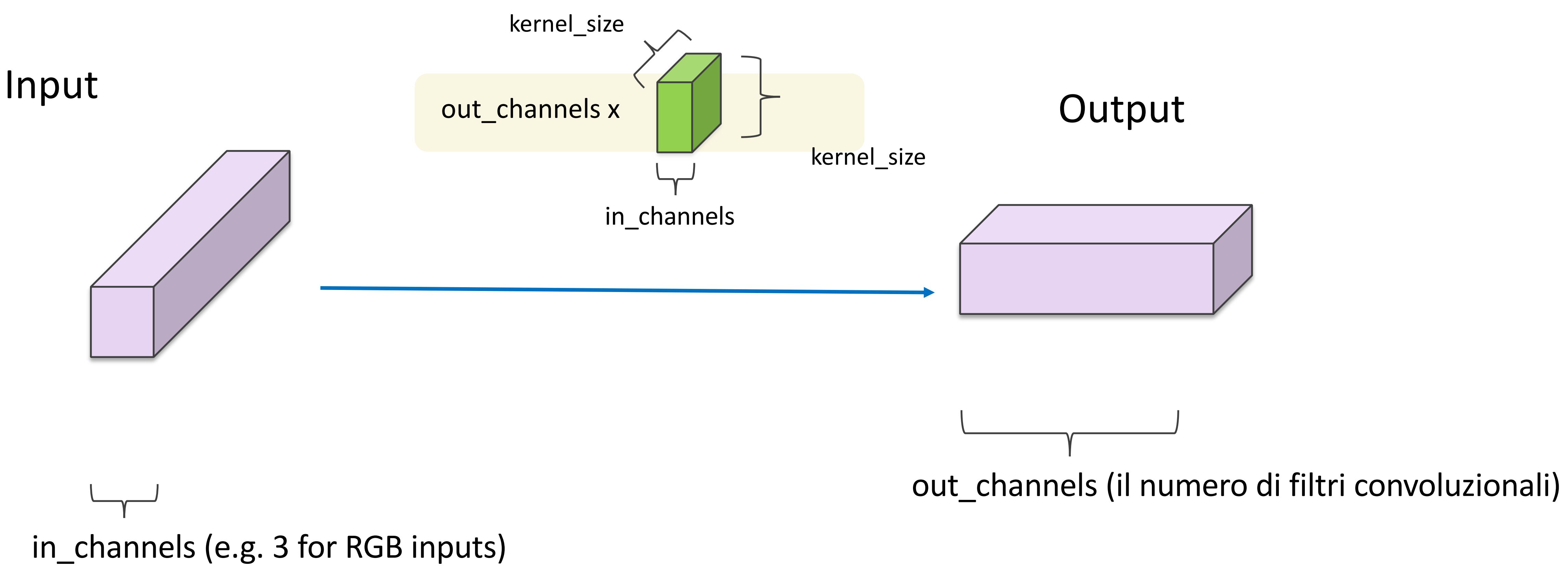
- Multiple feature maps, multiple poolings
- Max, average, L2, …

Convolutional neural networks

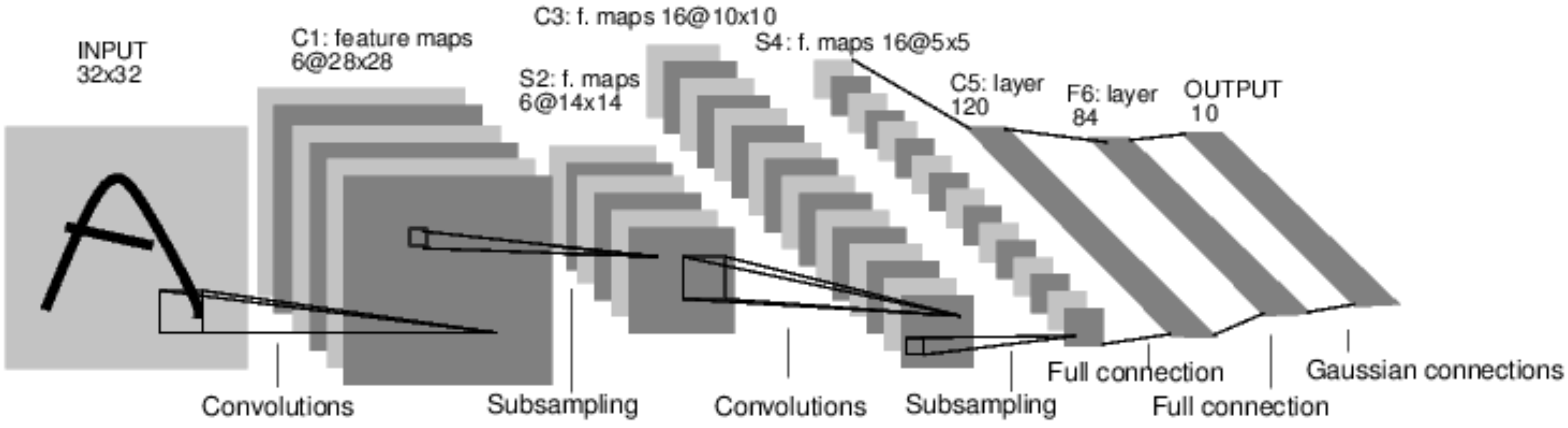


Convolutional Layer in pytorch

class `torch.nn.Conv2d`(*in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True*) [source]



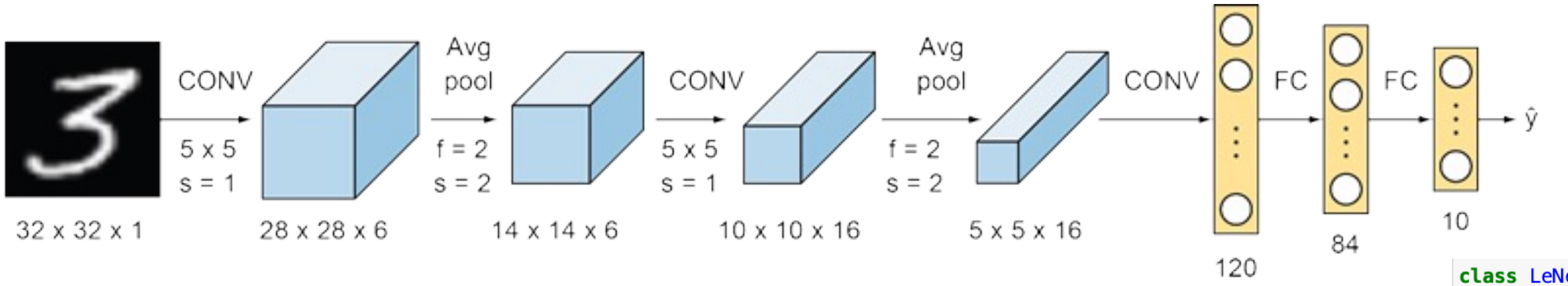
Convolutional Network: LeNet



Yann LeCun

TITLE	CITED BY	YEAR
Gradient-based learning applied to document recognition Y LeCun, L Bottou, Y Bengio, P Haffner Proceedings of the IEEE 86 (11), 2278-2324	11736	1998

LeNet in Pytorch




```python
class LeNet(nn.Module):
    def __init__(self,input_size):
        super(LeNet, self).__init__()
        # Convolutional Layers
        self.features = nn.Sequential(
            nn.Conv2d(1, 6, 5),
            nn.Tanh(),
            nn.AvgPool2d(2,stride = 2),
            nn.Conv2d(6, 16, 5),
            nn.Tanh(),
            nn.MaxPool2d(2,stride = 2)
        )
        fm_size = ((input_size - 6 )//2 - 5)//2 + 1
        fc_layer_in_size = 16*fm_size*fm_size

        # Linear layers
        self.fc = nn.Sequential(
            nn.Linear(fc_layer_in_size, 120),
            nn.Tanh(),
            nn.Linear(120, 84),
            nn.Tanh(),
            nn.Linear(84, 10)
        )


    def forward(self, x):
        features = self.features(x)

        # Flatten the tensor along the second dimension
        features_flattened = features.view(features.size(0),-1)

        out = self.fc(features_flattened)

        output = F.log_softmax(out, dim=1)

        return output
```

LeNet Summary

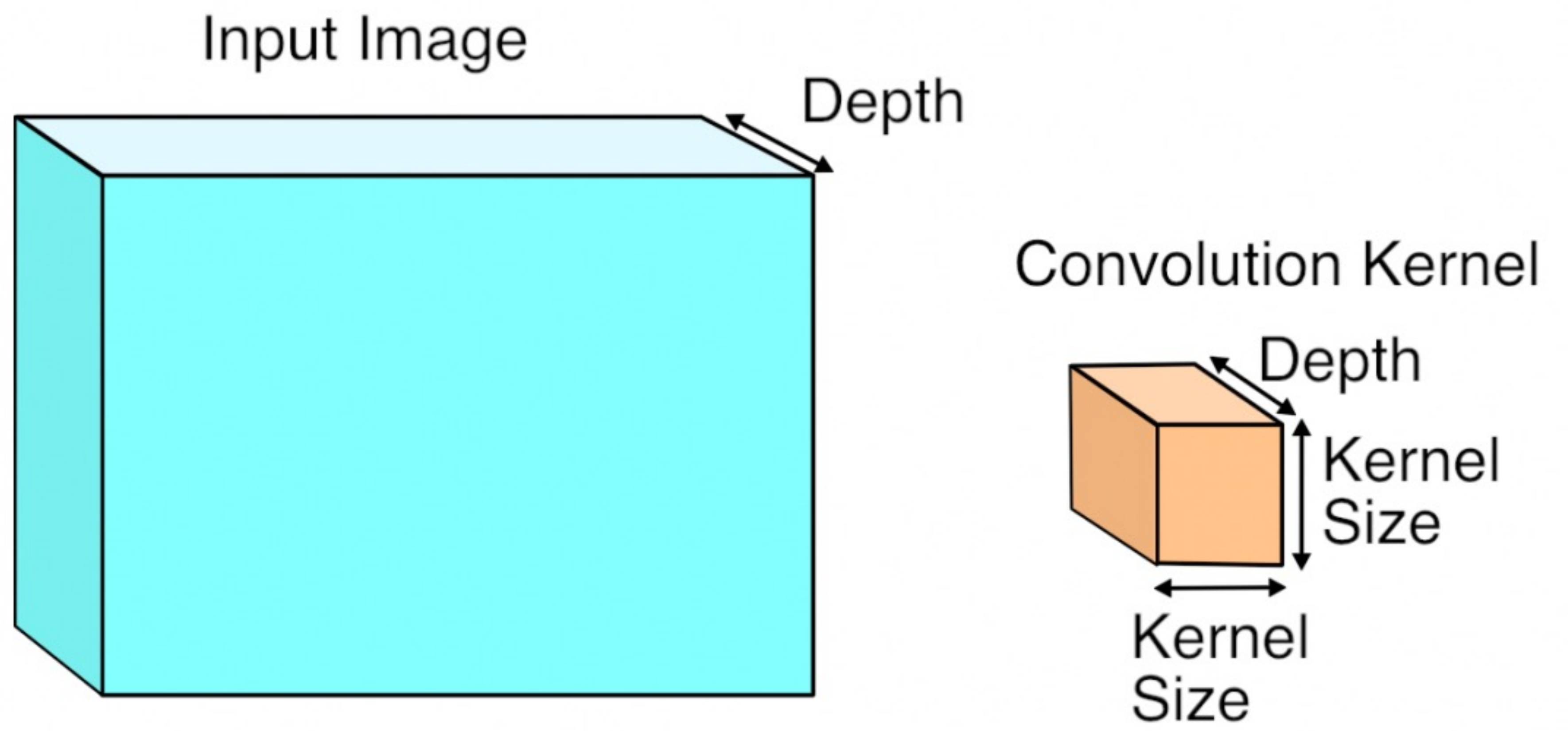
- 2 Convolutional Layers + 3 Linear Layers

- + Non-linear functions: ReLUs or Sigmoids
  + Max-pooling operations

Esercizio

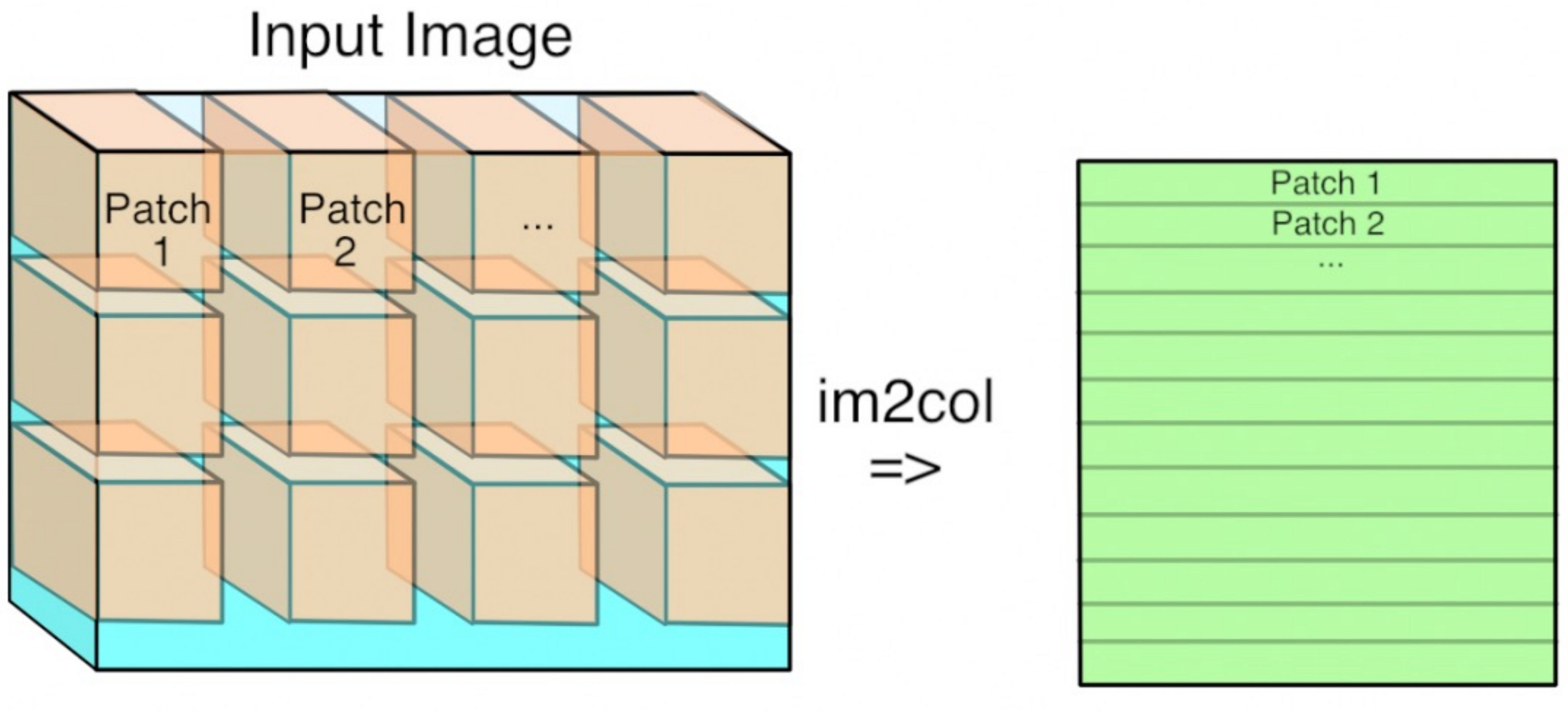
- Adattare la rete LeNet per effettuare classificazione sul dataset CIFAR10
  - CIFAR-10 consiste di 60000 immagini 32x32 (RGB), etichettate con un intero che corrisponde a 10 classi: airplane (0), automobile (1), bird (2), cat (3), deer (4), dog (5), frog (6), horse (7), ship (8), truck (9).

Convolutional Layers, Matrix Multiplication



https://petewarden.com/2015/04/20/why-gemm-is-at-the-heart-of-deep-learning/

Convolutional Layers, Matrix Multiplication



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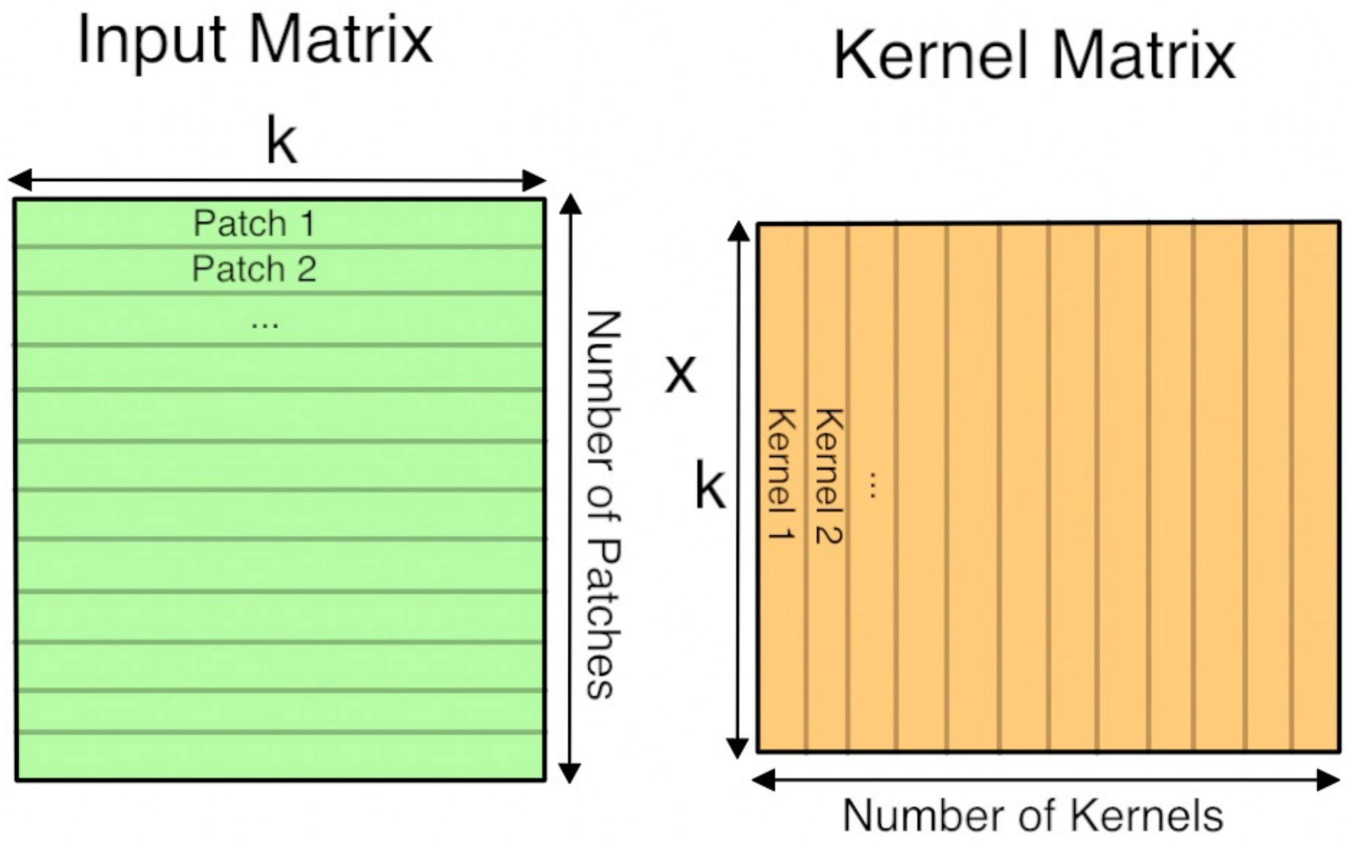

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Conviene usare le CNN?

- Altamente parallelizzabili
- GPU Computing
- CPU Computing proibitivo

Perché CNNs?

- Sparse interactions
  - Meno parametri
- Parameter sharing
  - Kernel condivisi lungo tutta l'immagine
- Invarianza di traslazione
- Possibilità di lavorare con input di dimensione variabile