Analisi di Immagini e Video (Computer Vision)

Giuseppe Manco

Outline

- Segmentation
- Approcci classici
- Deep Learning for Segmentation

Crediti

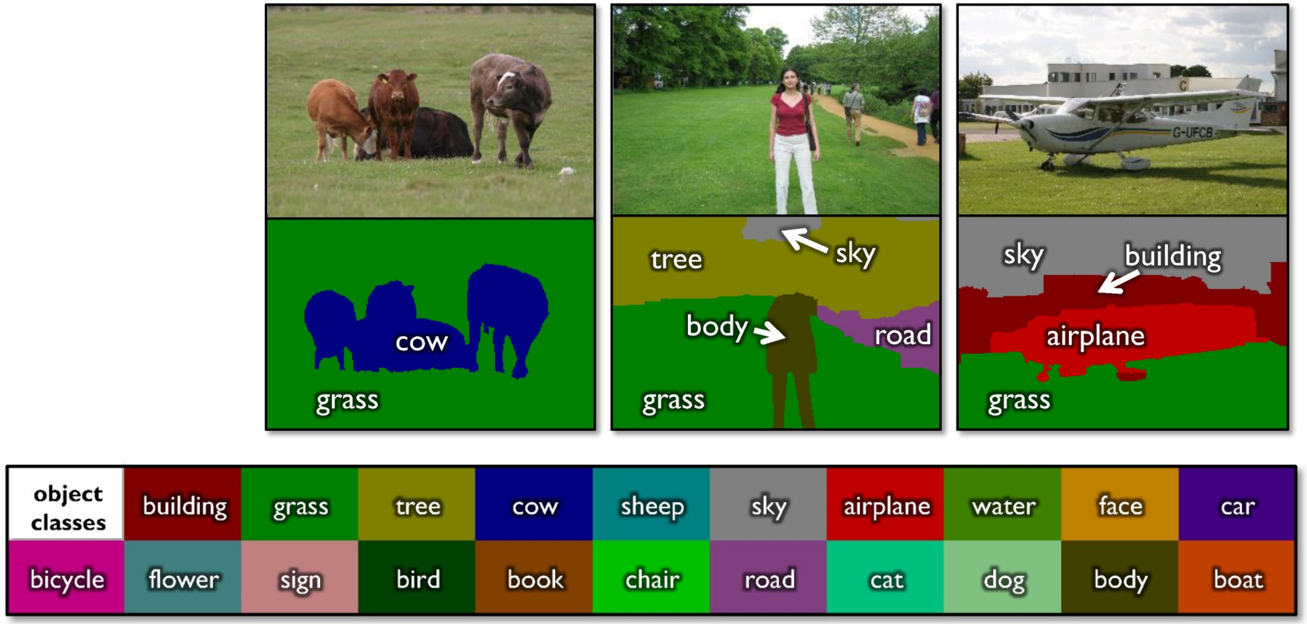
- Slides adattate da vari corsi e libri
  - Computational Visual Recognition (V. Ordonez), CS Virgina Edu
  - Computer Vision (S. Lazebnik), CS Illinois Edu

Approcci supervisionati

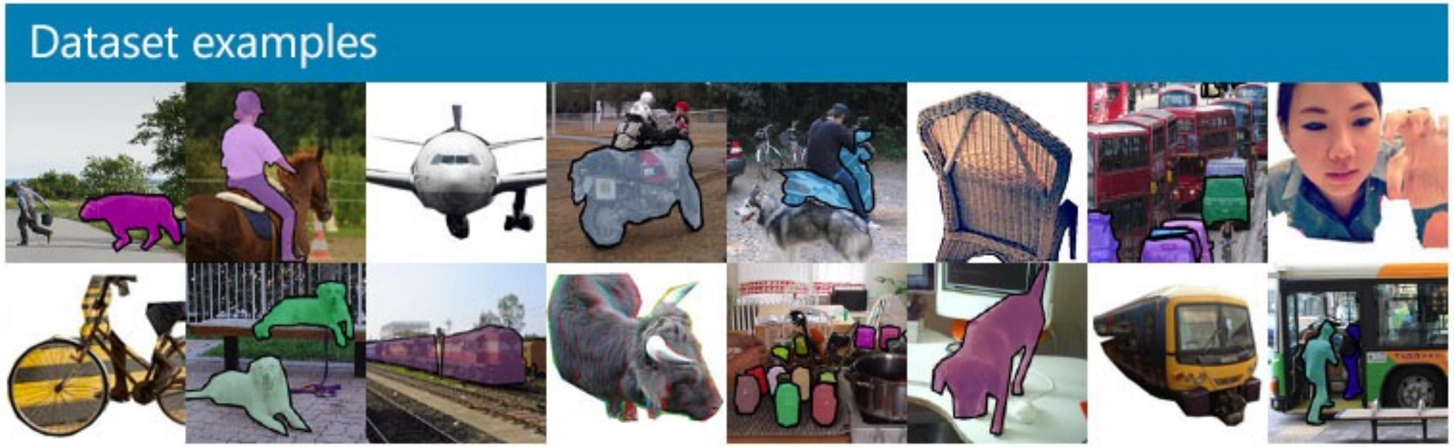
- L'approccio basato su CRF è semi-supervisionato
- Possiamo renderlo supervisionato?
  - Parametrizziamo gli unary e binary potentials
    - E.g., $p(y_i|x_i;\theta) = \frac{1}{Z}\exp\left(w_{y_i} \cdot F(x_i)\right)$
  - Apprendiamo i parametri che minimizzano l'energia media su tutti gli esempi

Semantic segmentation, object detection

- Problema
  - Etichettare ogni pixel con una classe
  - Multi-class problem
- Utilizzo di dati già etichettati
  - Pascal VOC
  - MS COCO



MS-COCO



- Large-scale dataset for object detection, segmentation and captioning
  - 330K images (>200K labeled)
  - 1.5 million object instances
  - 80 object categories
  - 91 stuff categories
  - 5 captions per image
  - 250,000 people with keypoints

Perché Deep Learning?

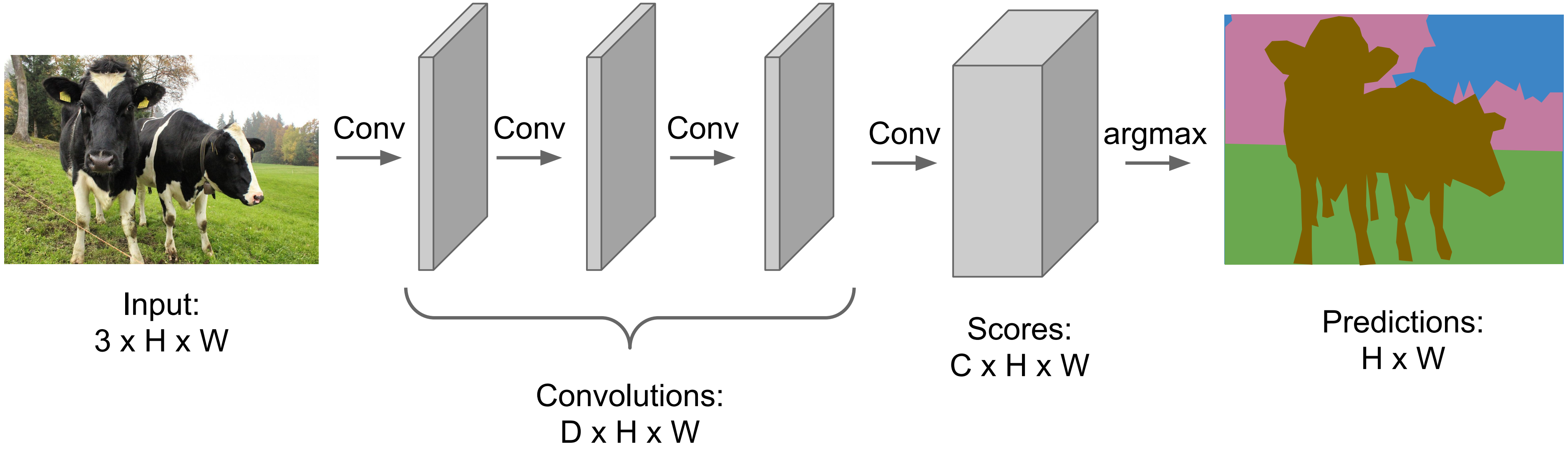
- Stesso principio dell’object detection
  - Convolutional features, learned from training data
- Accuratezza
- Velocità

Approcci

- Approcci downsampling-upsampling
- Metodi multi-scala

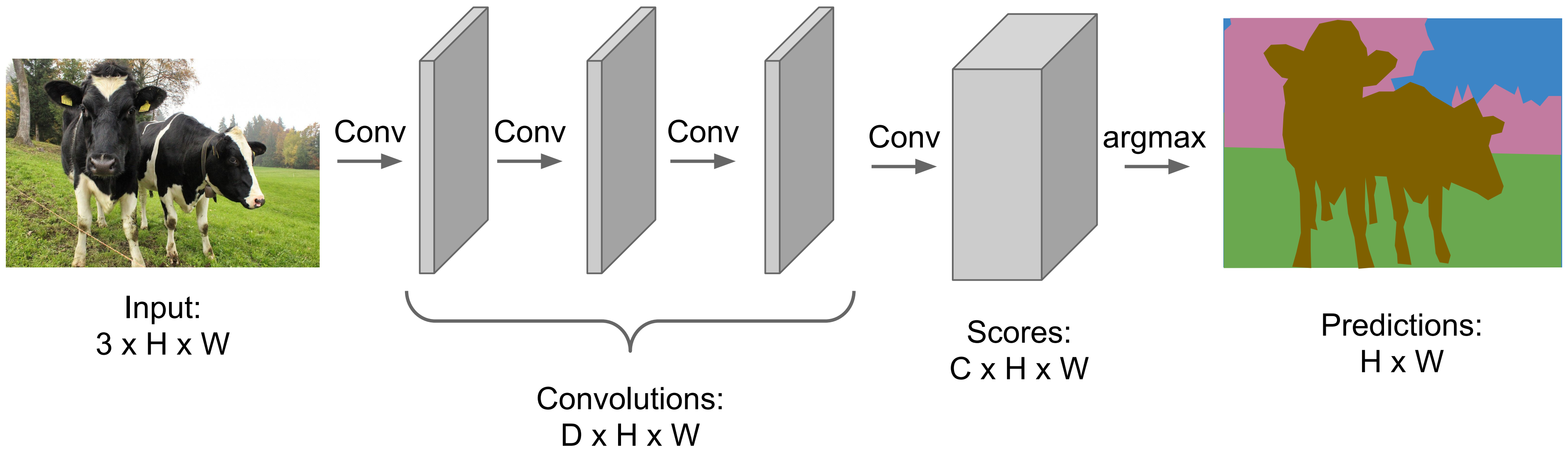
Fully Convolutional Networks

- Utilizziamo i layer convoluzionali per fare le predizioni sui vari pixel



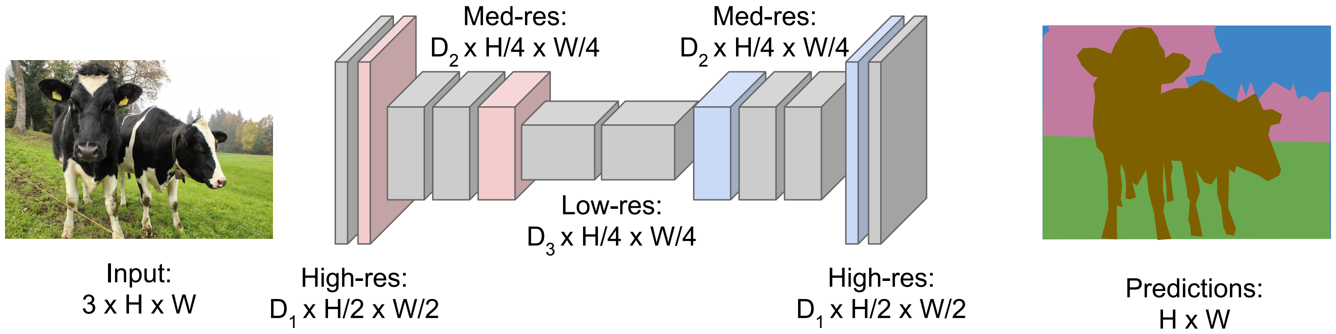
Fully Convolutional Networks

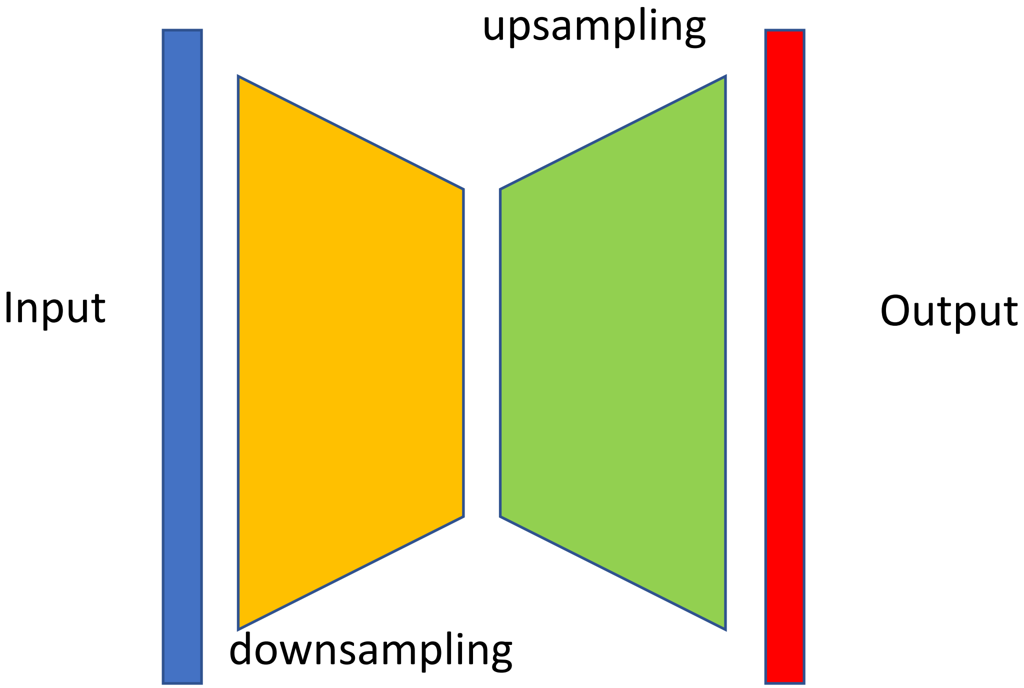
- Utilizziamo i layer convoluzionali per fare le predizioni sui vari pixel
  - Ma fare convoluzioni su feature map grandi è costoso



Fully Convolutional Networks

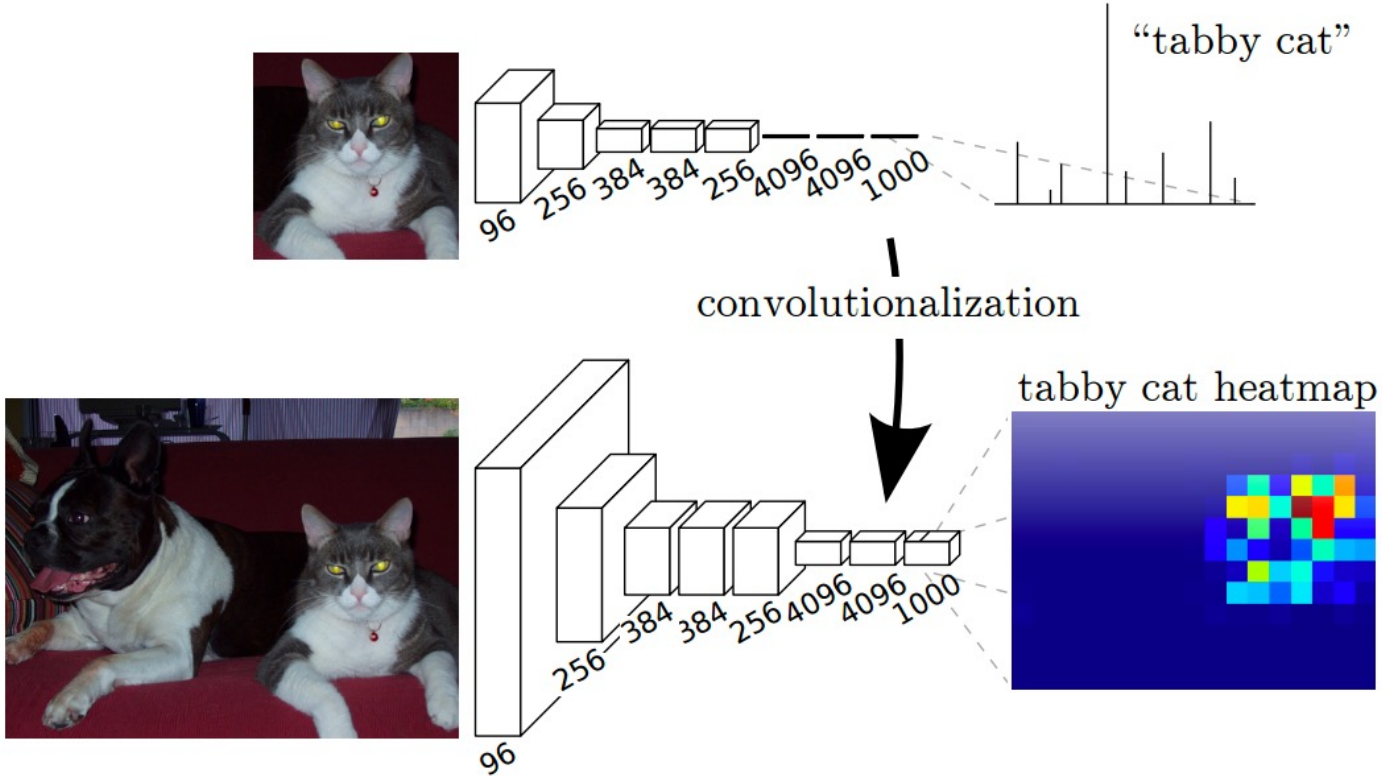
- Soluzione
  - Architettura Encoder-Decoder





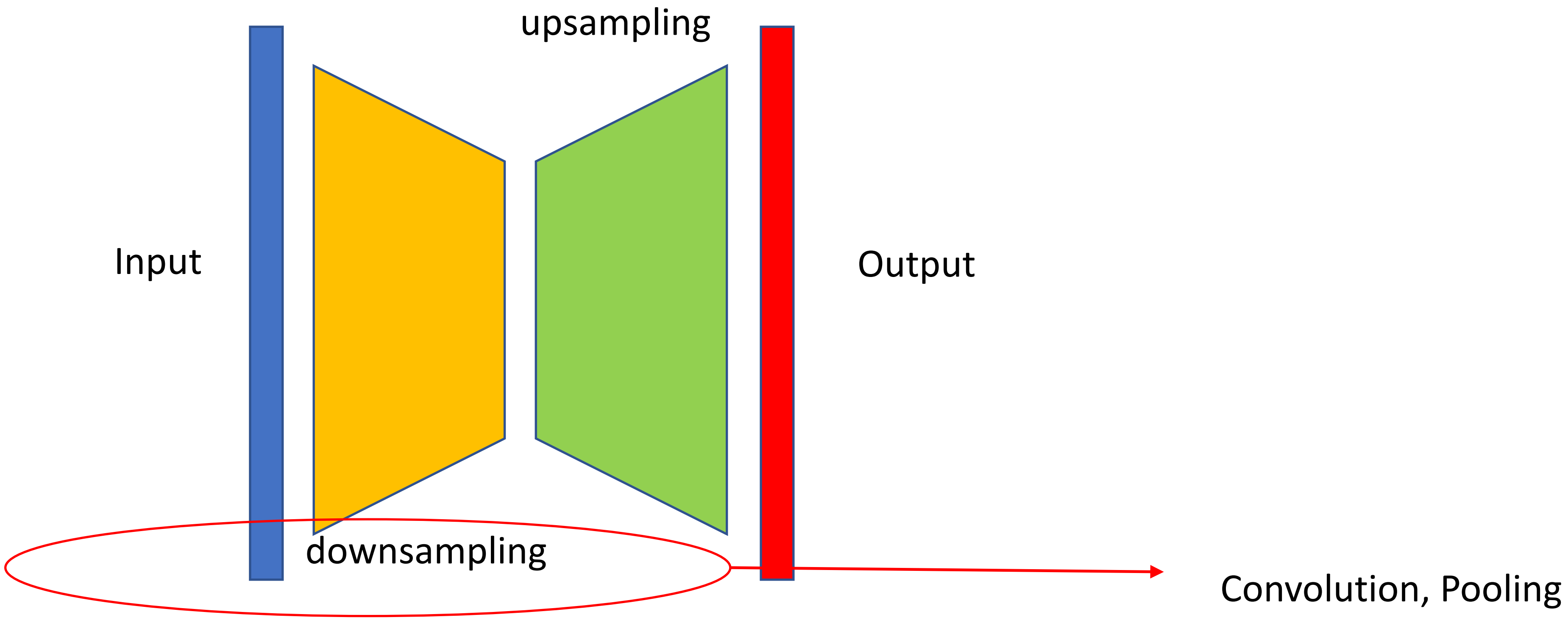
Convolutionalization

- Fully Convolutional Layers
- Faster-RCNN, SSD



Fully Convolutional Networks

- Architettura Encoder-Decoder



Fully Convolutional Networks

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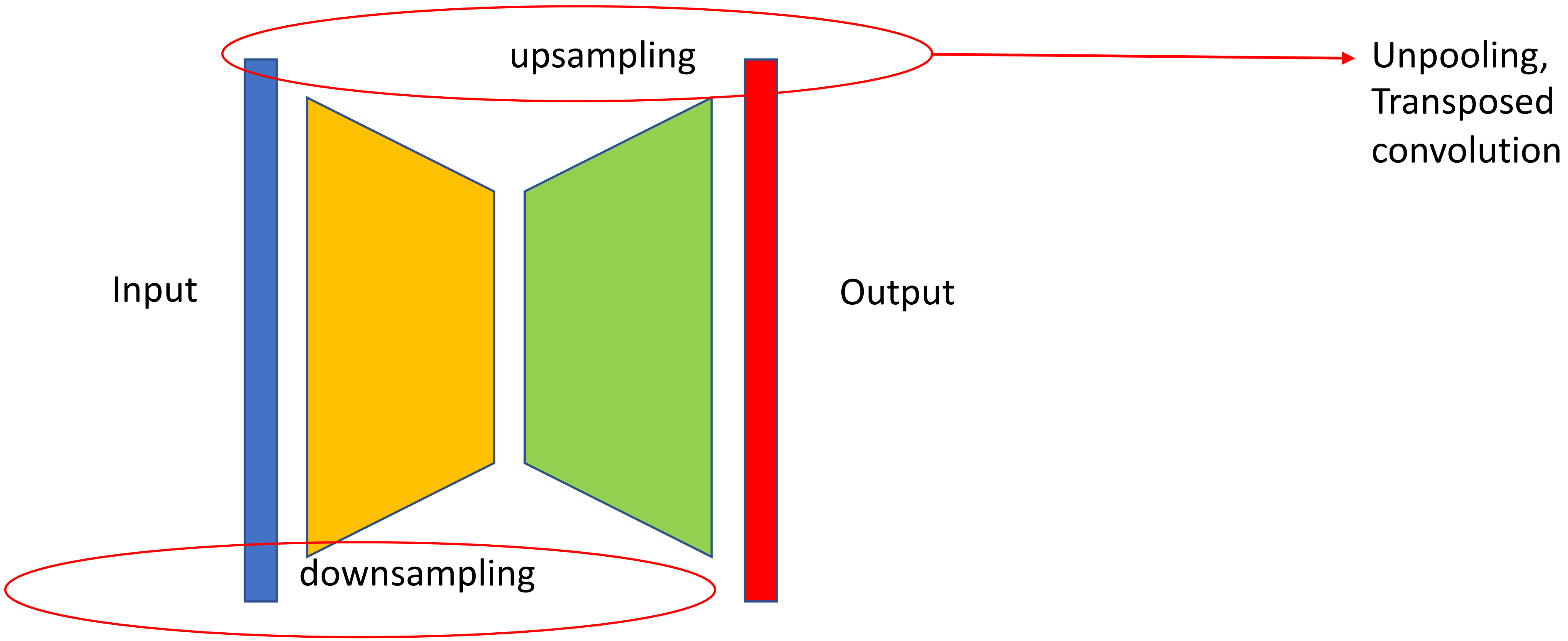
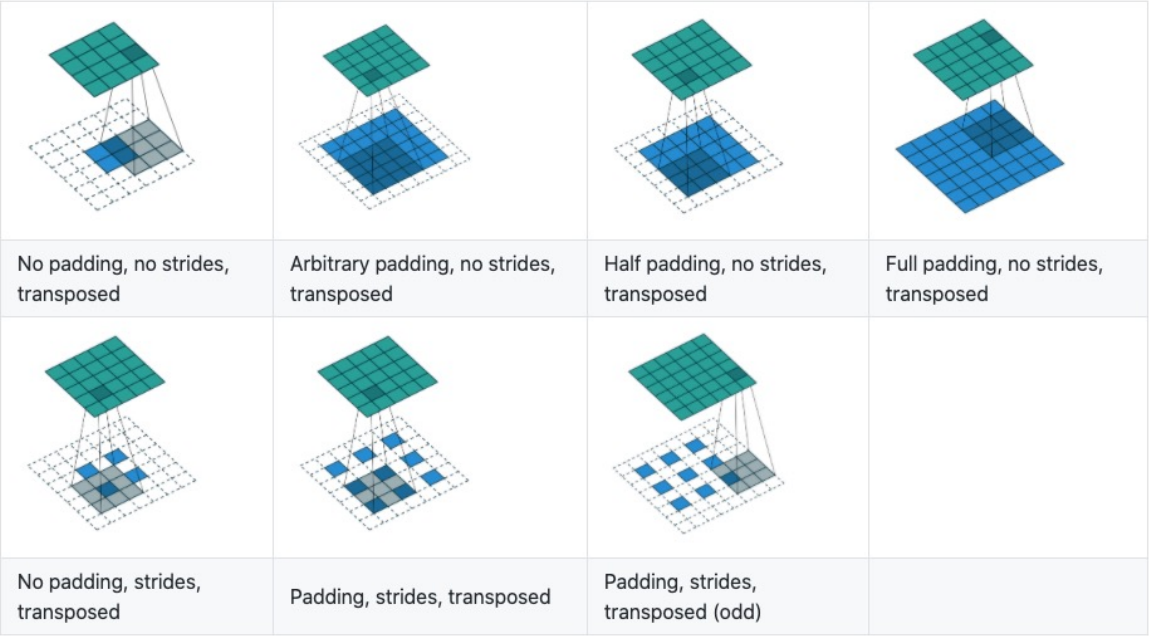


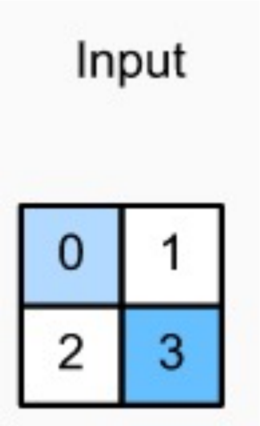
Up-sampling Convolutions

- Upsampling
  - Da un’input a bassa risoluzione si passa ad uno a più alta risoluzione
  - Transposed Convolution
    - Qual è la relazione?
      - Suggerimento: invertiamo le relazioni originarie

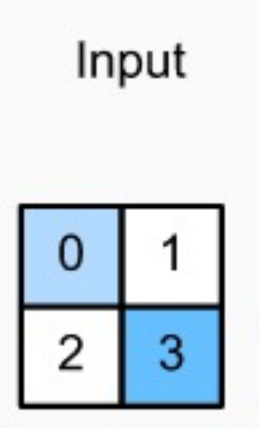


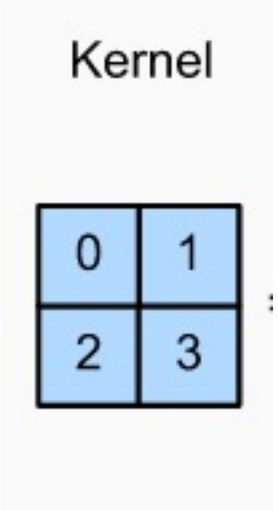
https://github.com/vdumoulin/conv_arithmetic

Transposed Convolution



Transposed Convolution





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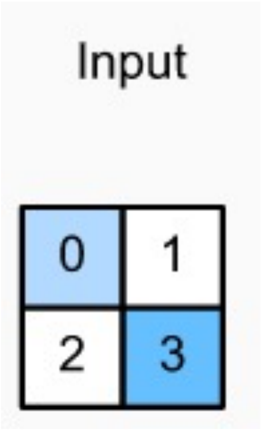
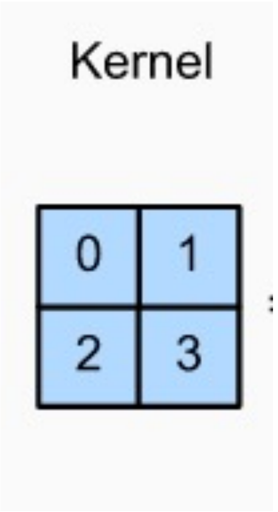
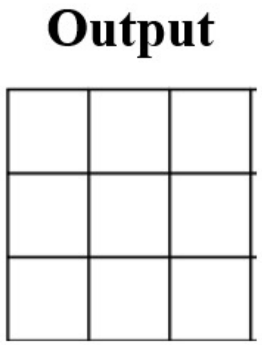
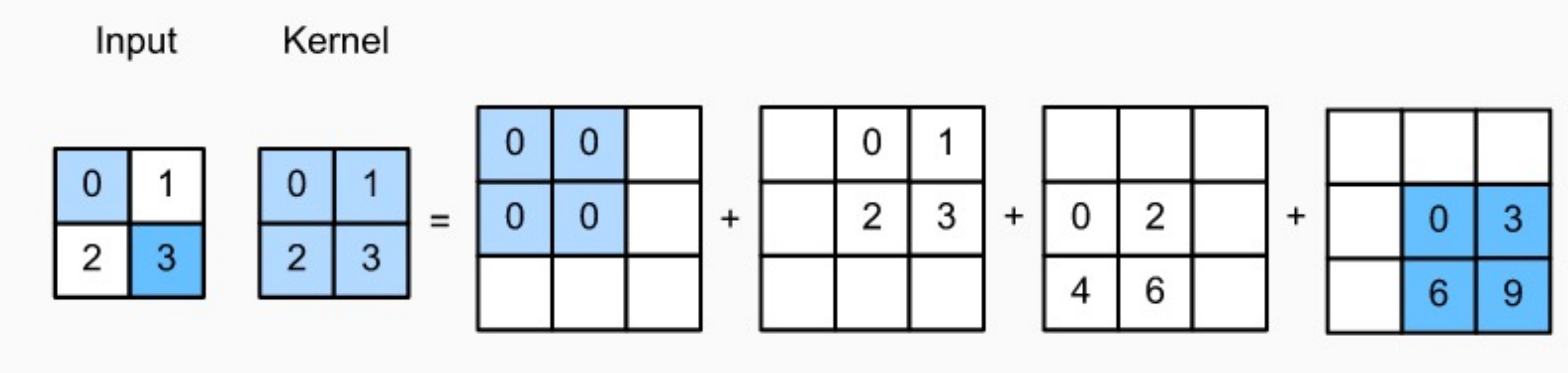






Transposed Convolution

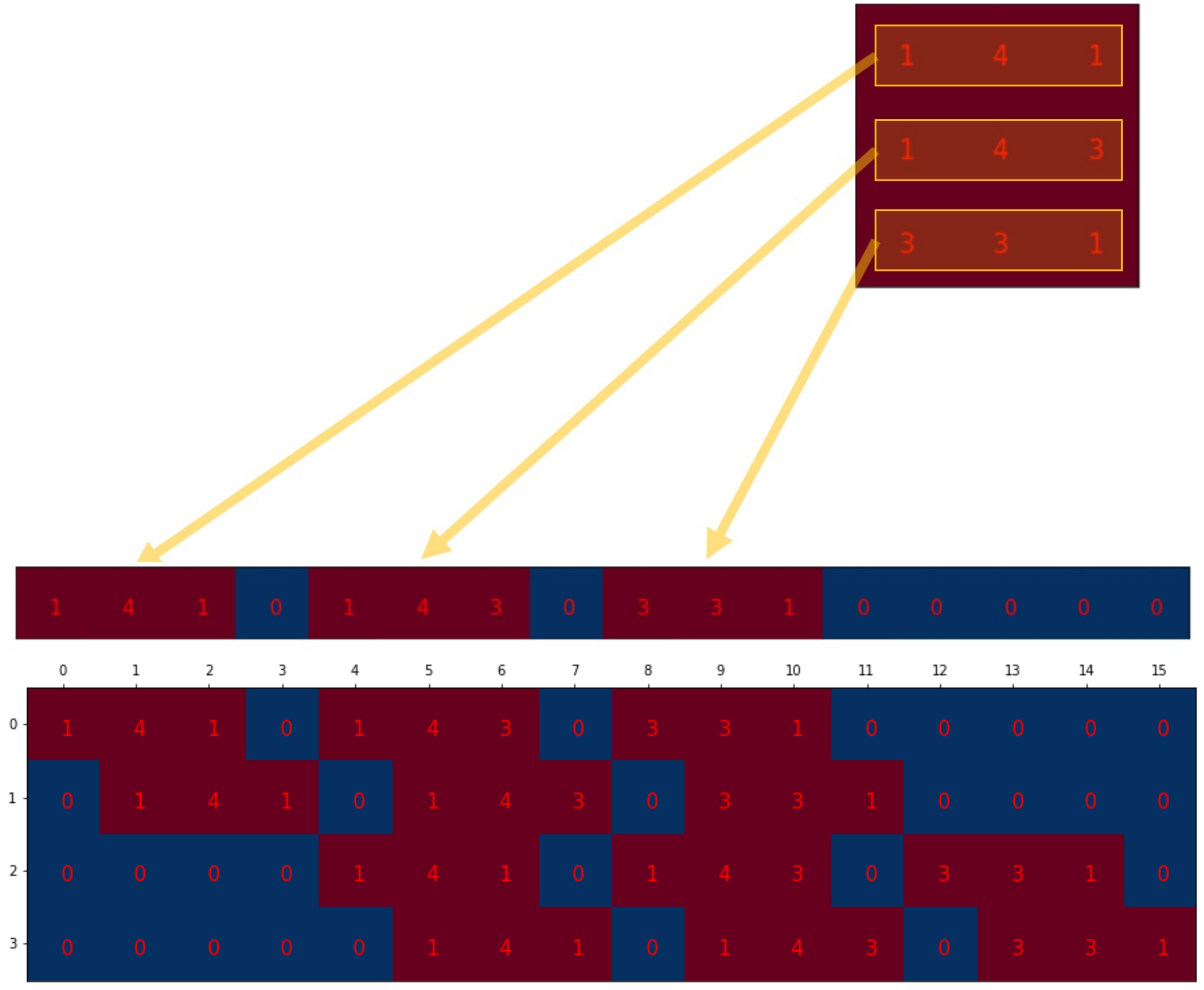
- Ogni valore si distribuisce su un intorno dell’output in base al kernel.



- La distribuzione viene guidata da padding e stride

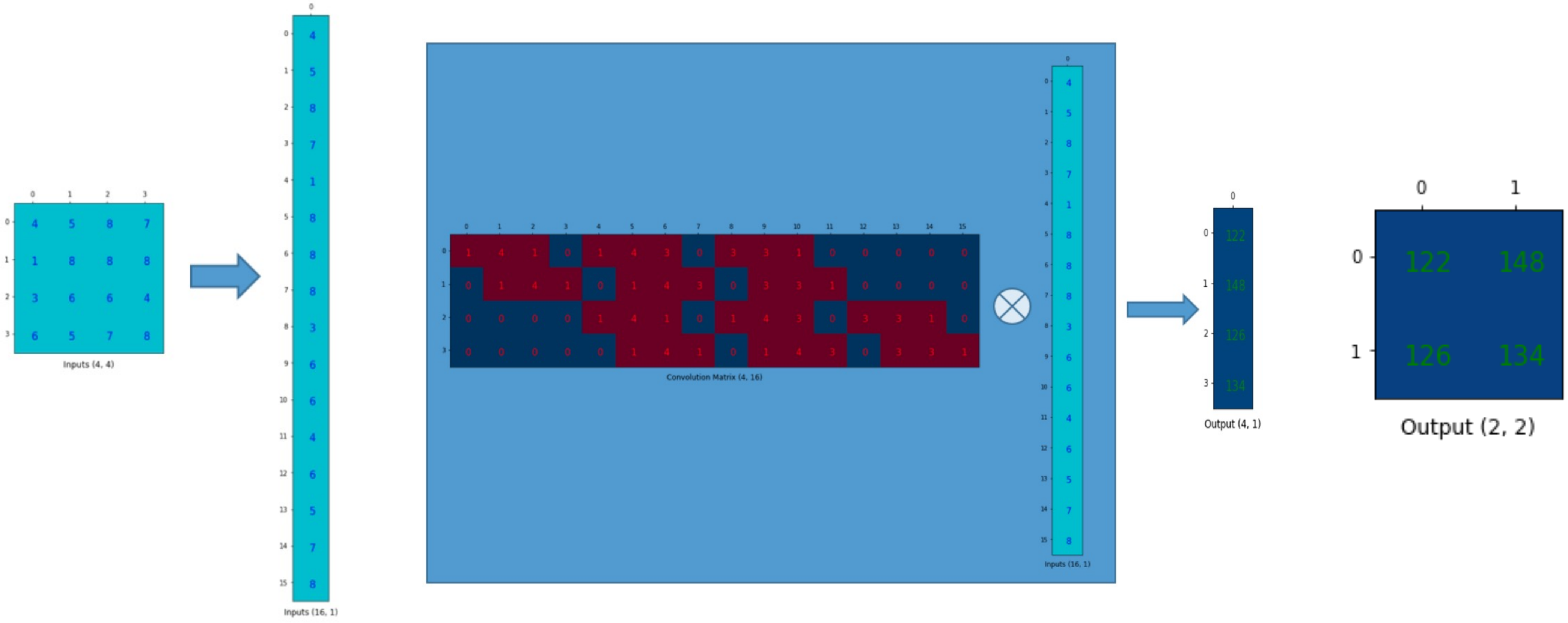
Convolution e transposed convolution

- Ogni riga definisce un’operazione di convoluzione
  - Filtro 3x3, input 4x4
    - No padding, no strides, no dilation



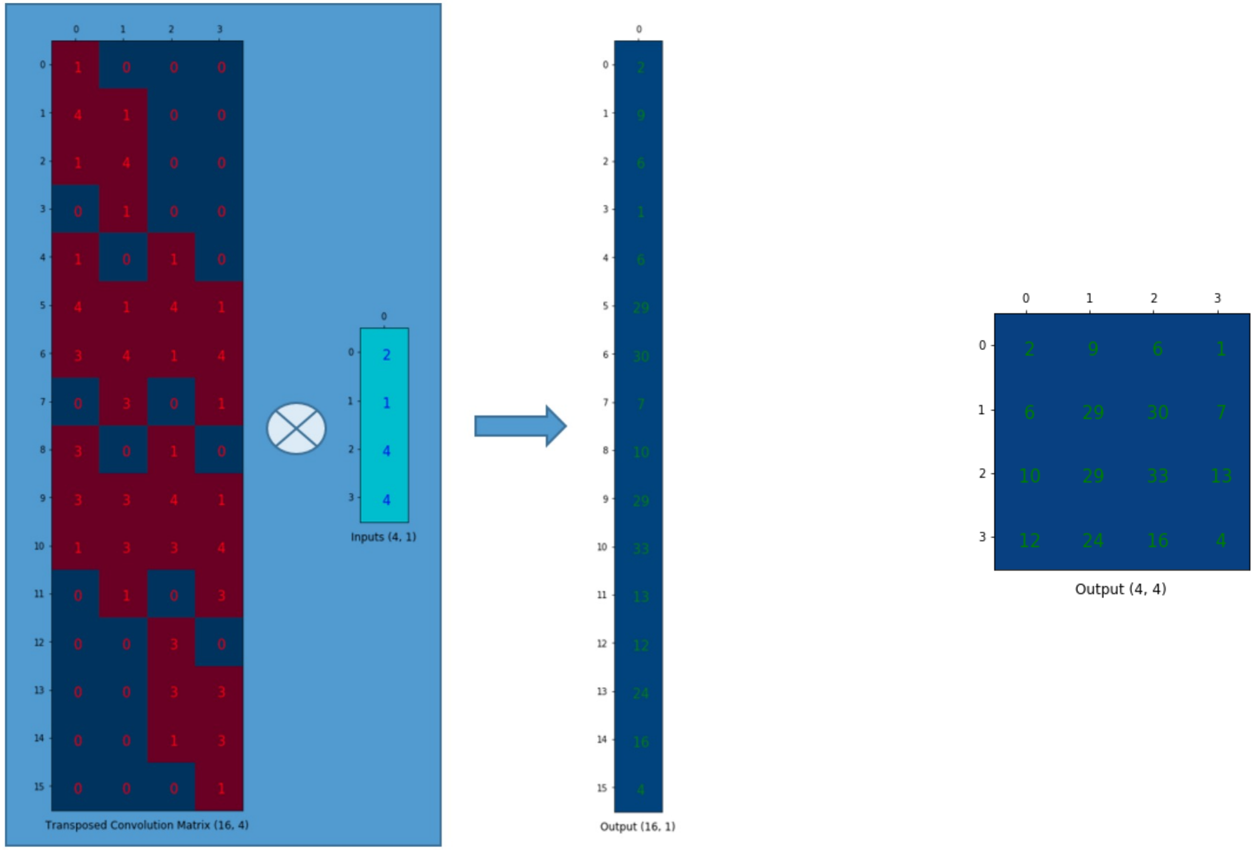
Convolution e transposed convolution

- Ogni riga definisce un’operazione di convoluzione



Convolution e transposed convolution

- Trasponendo la matrice di convoluzione, otteniamo l'operazione opposta



ConvTranspose, Padding

- Decrementa l’output della TD
  - Interpretazione: l’ammontare di padding che l’input richiede per completare l’output
  - Quale sarebbe l’output dell’esempio precedente?

Input

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	1	3	2	1	0	0
0	0	1	3	3	1	0	0
0	0	2	1	1	3	0	0
0	0	3	2	3	3	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Kernel

1	2	3
0	1	0
2	1	2

Output

1	5	11	14	8	3
1	6	15	18	12	3
4	13	21	21	15	11
5	17	28	27	25	11
4	7	9	12	8	6
6	7	14	13	9	6

Input

1	3	2	1
1	3	3	1
2	1	1	3
3	2	3	3

Kernel

1	2	3
0	1	0
2	1	2

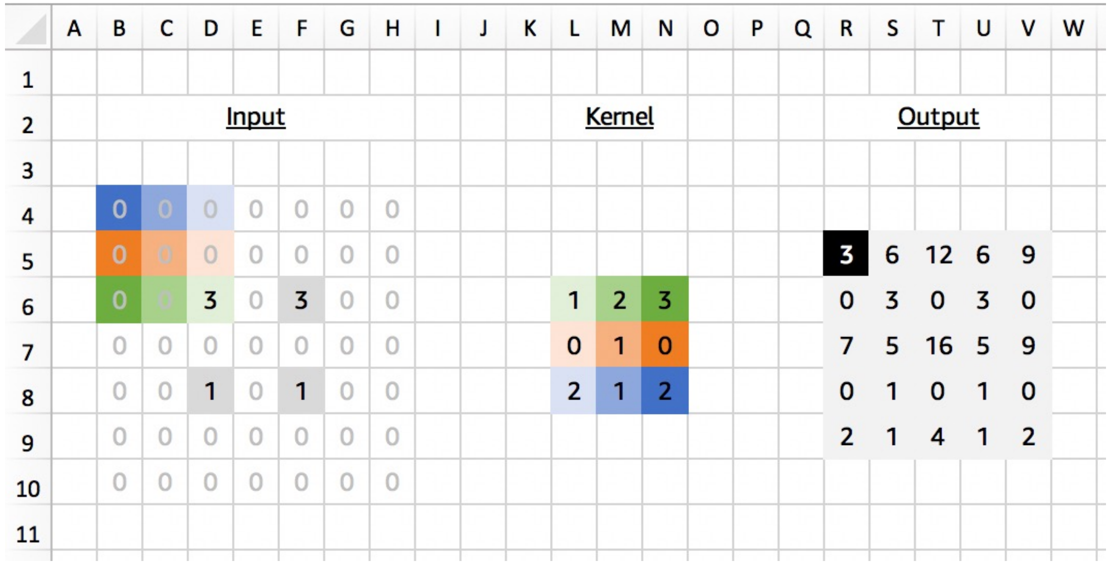
Output

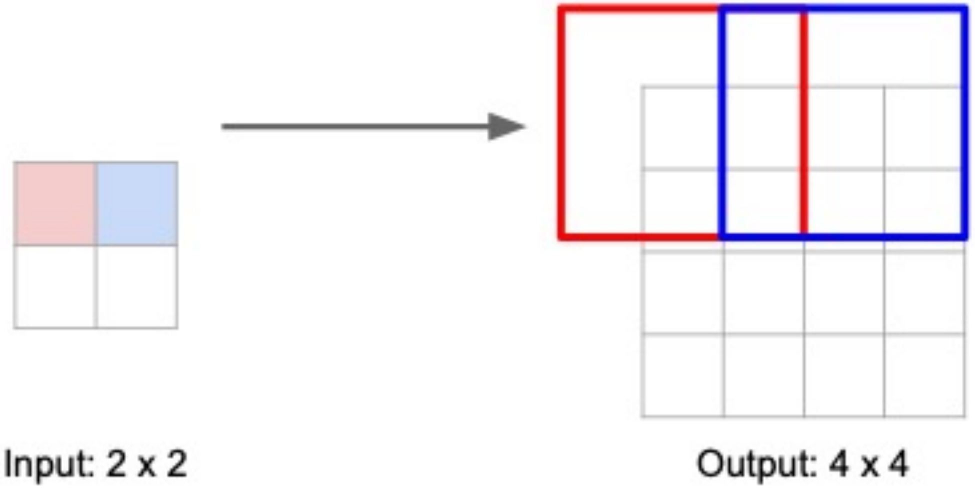
21	21
28	27

ConvTranspose, Stride

- Espande l'output
  - Di conseguenza «fraziona» l'input aggiungendo spazi

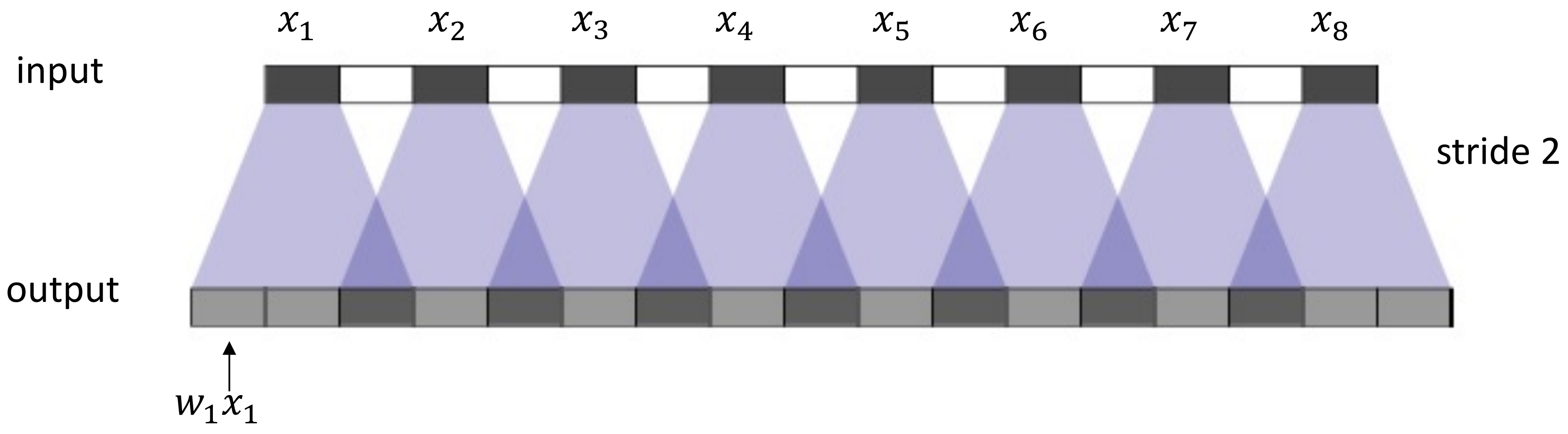
Il filtro si muove di 2 pixel sull'output





ConvTranspose, checkerboarding

- Filter $[w_1, w_2, w_3]$, *output stride* = 2



Animation: https://distill.pub/2016/deconv-checkerboard/

ConvTranspose, checkerboarding

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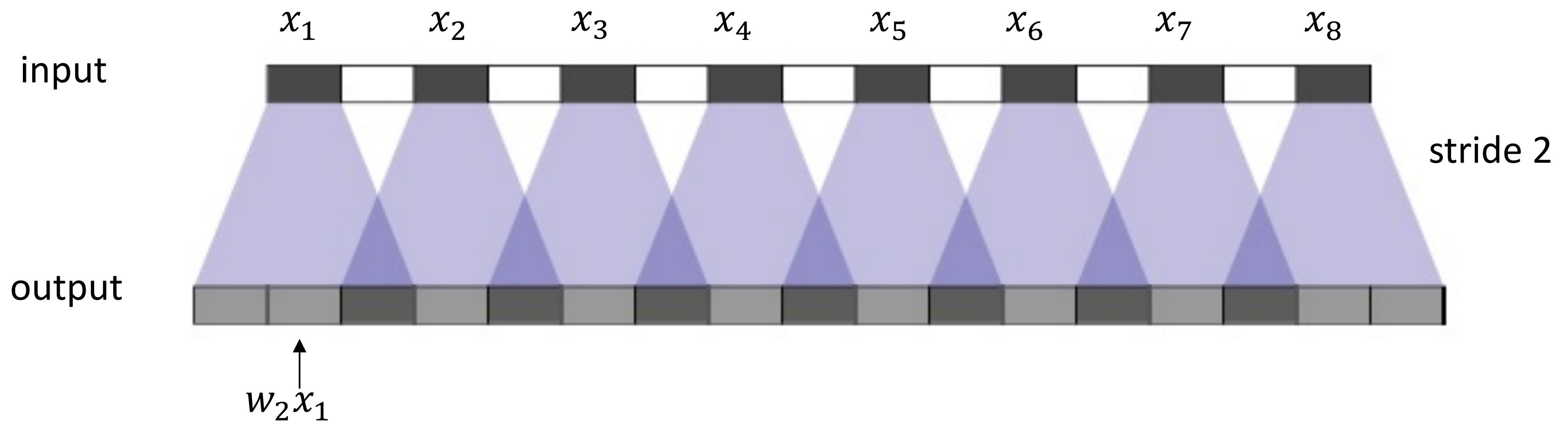

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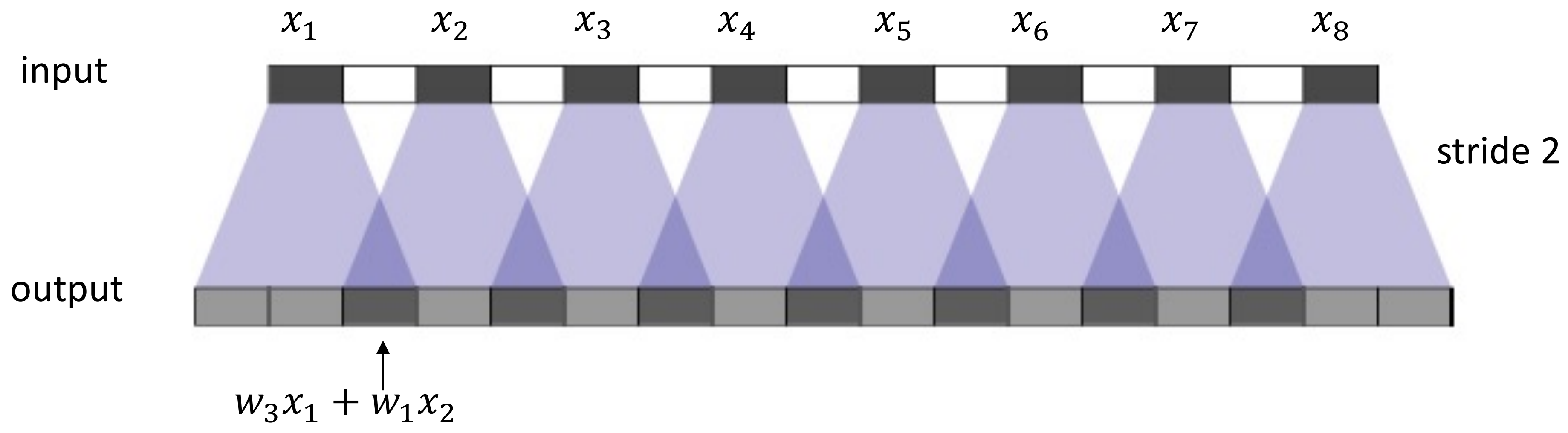

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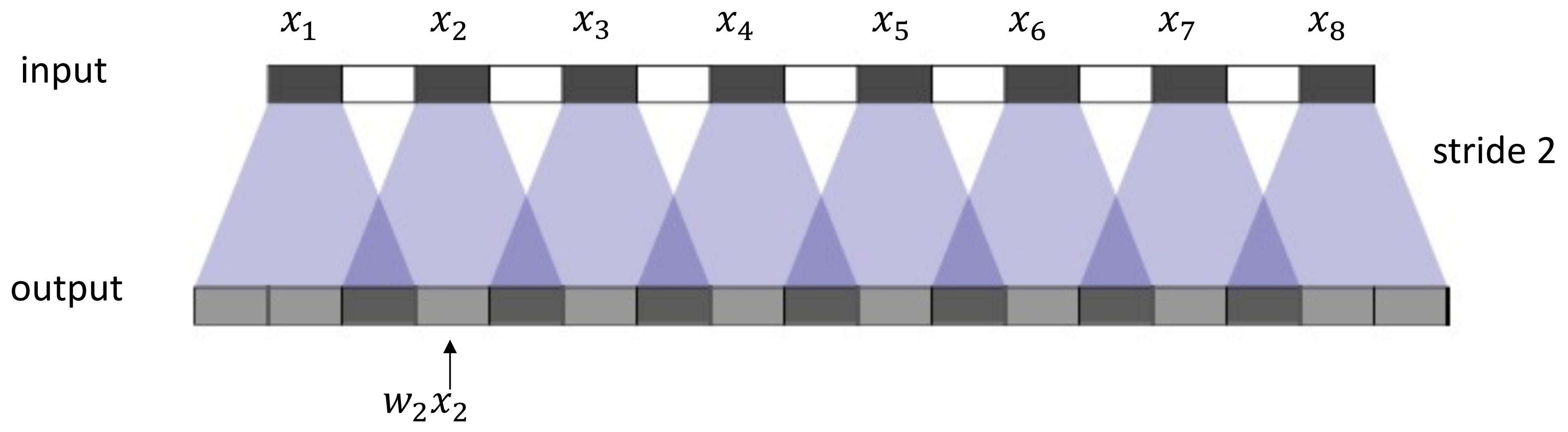

ConvTranspose, Checkerboarding

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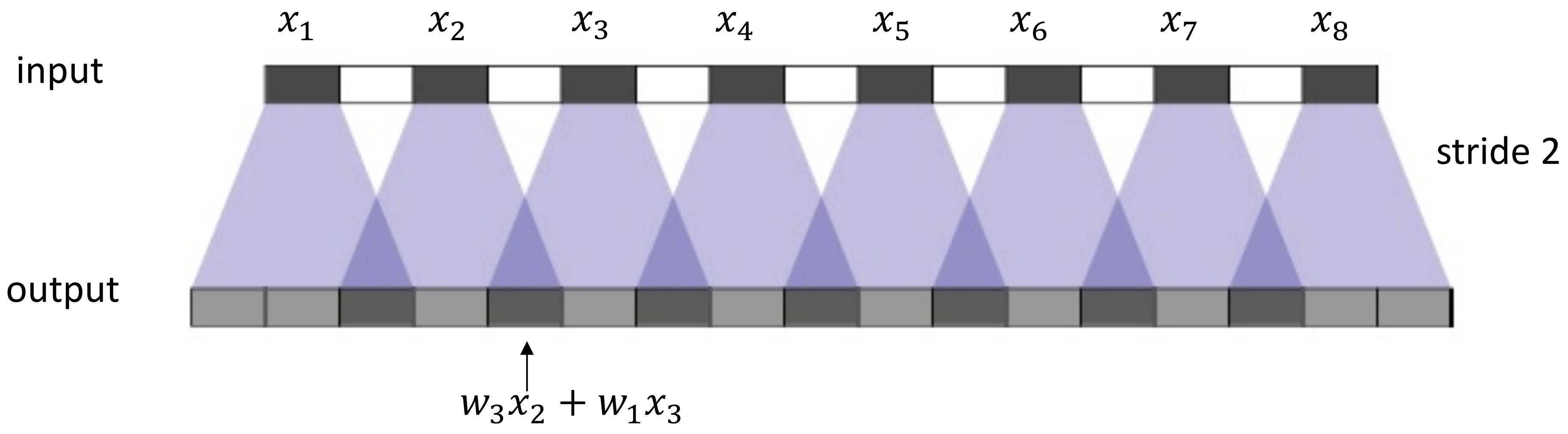
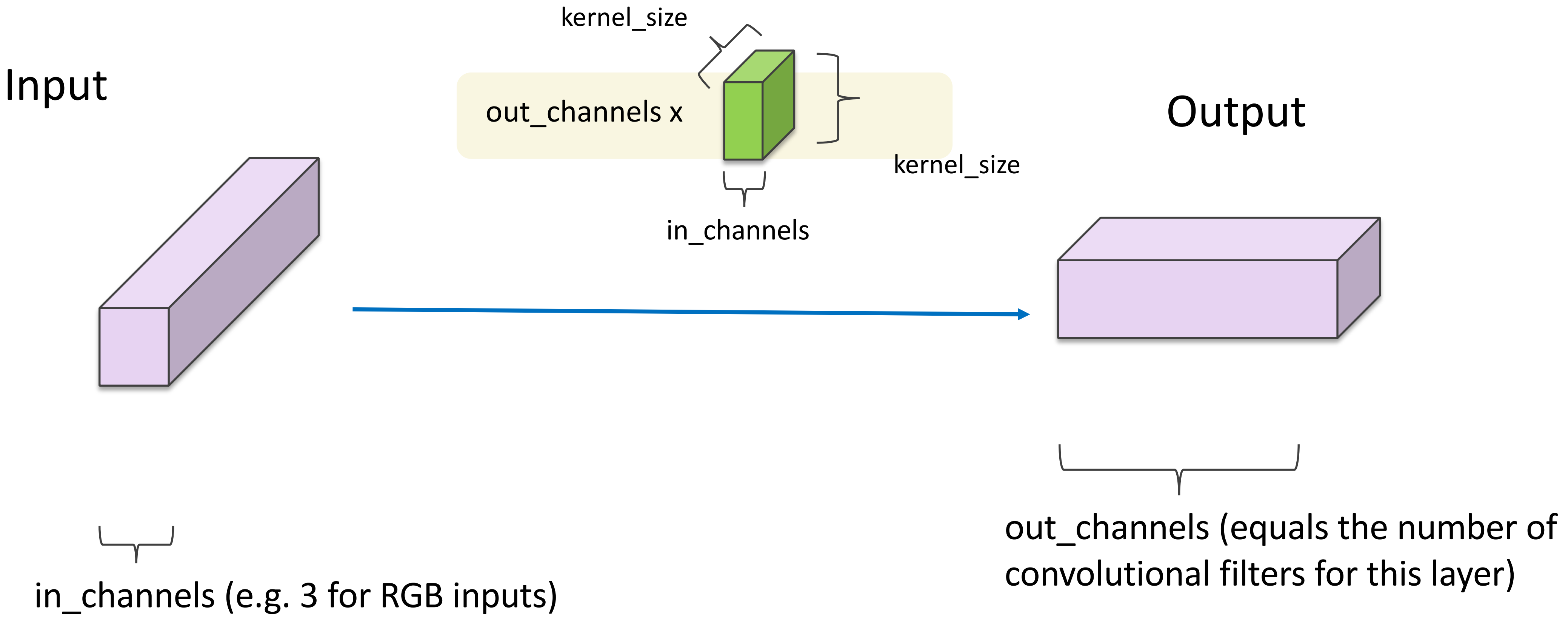


Transposed Convolution in Pytorch

```
CLASS torch.nn.ConvTranspose2d(in_channels, out_channels, kernel_size, stride=1, padding=0,
      output_padding=0, groups=1, bias=True, dilation=1, padding_mode='zeros')
```



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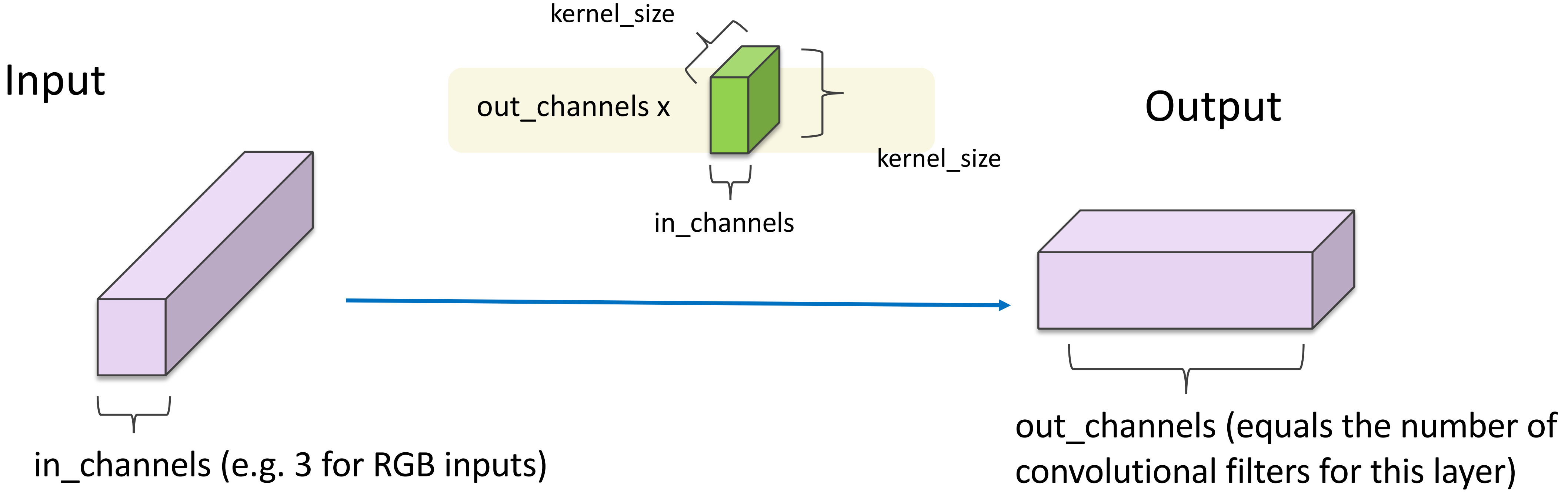
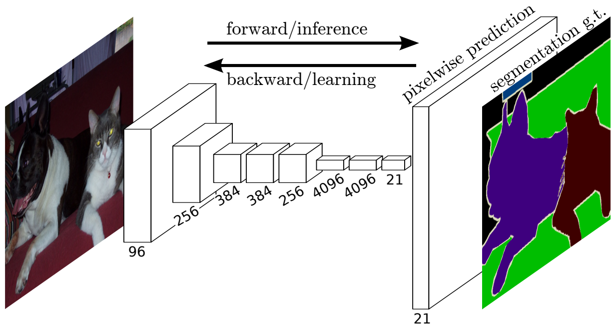
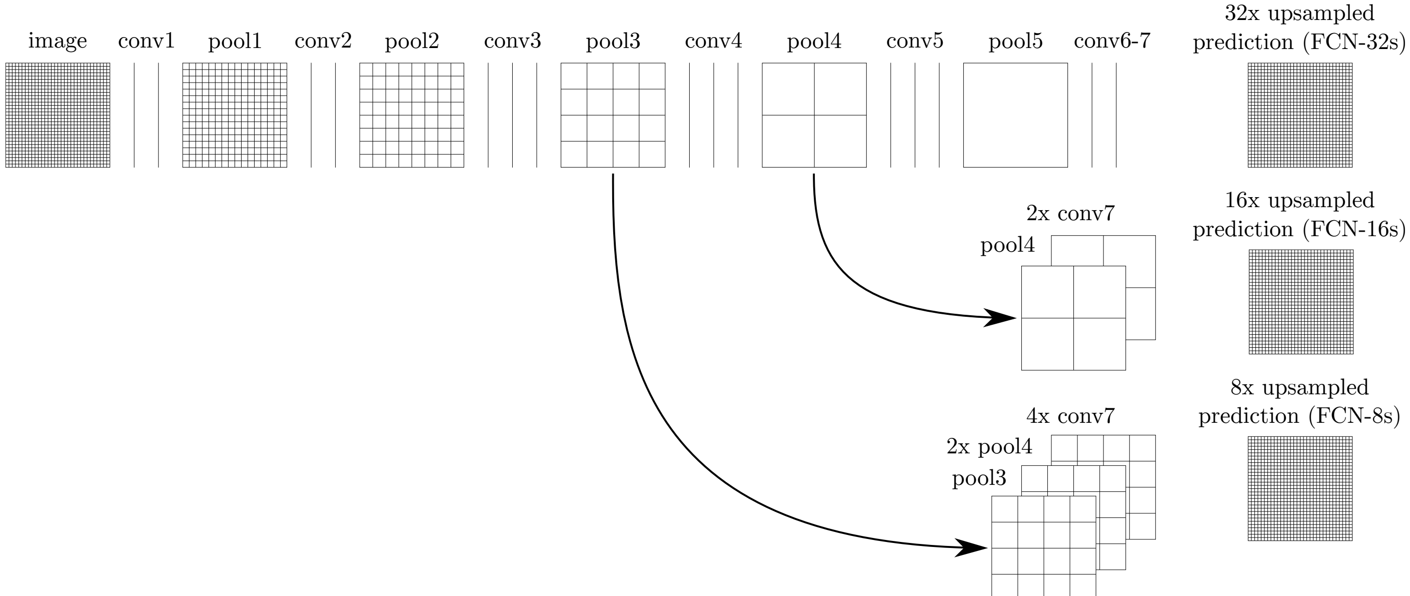


$$Out = (In - 1) \times \text{stride} - 2 \times \text{padding} + \text{dilation} \times (\text{kernel\_size} - 1) + \text{output\_padding} + 1$$

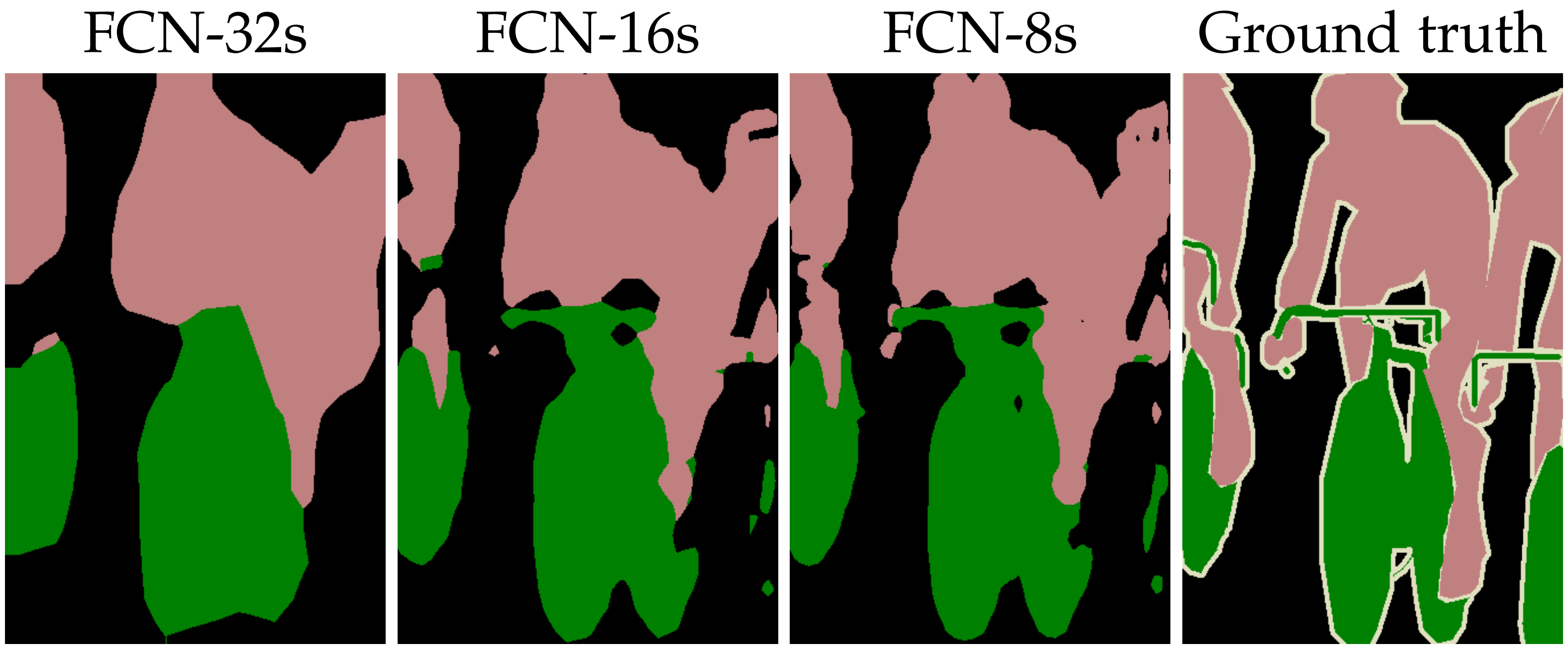
FCN: architettura

- Principio
  - Riduciamo la dimensione, facciamo upsampling
- Tre varianti
  - Coarse upsampling
  - Combined upsampling, skip connections (tramite somma)





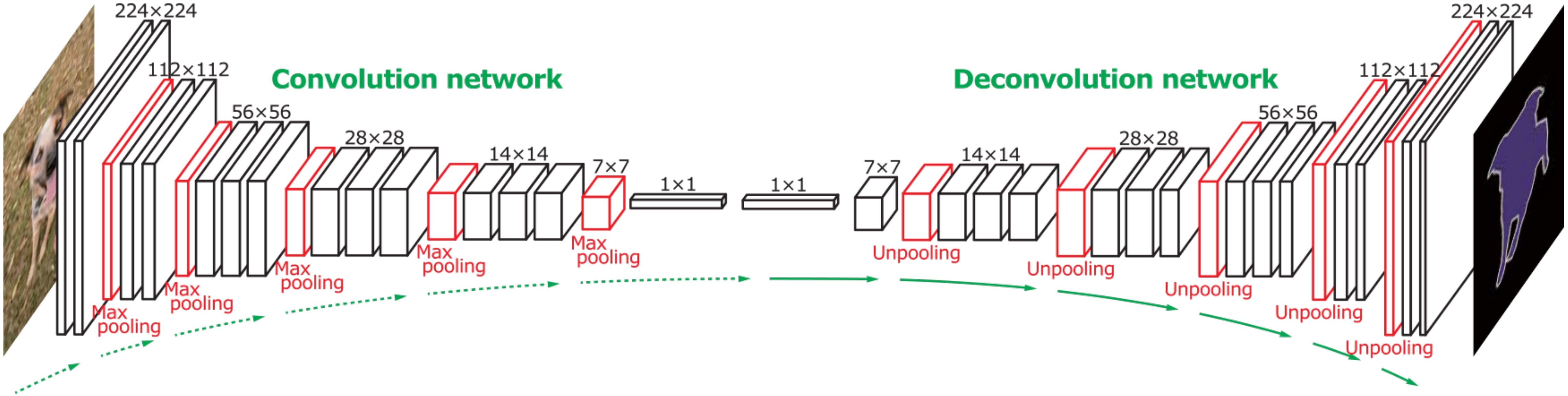
FCN



- L'utilizzo di ConvTranspose con stride di grandi dimensioni causa la presenza di artefatti
- Scarsa risoluzione ai bordi
  - L'encoding causa perdita di informazione

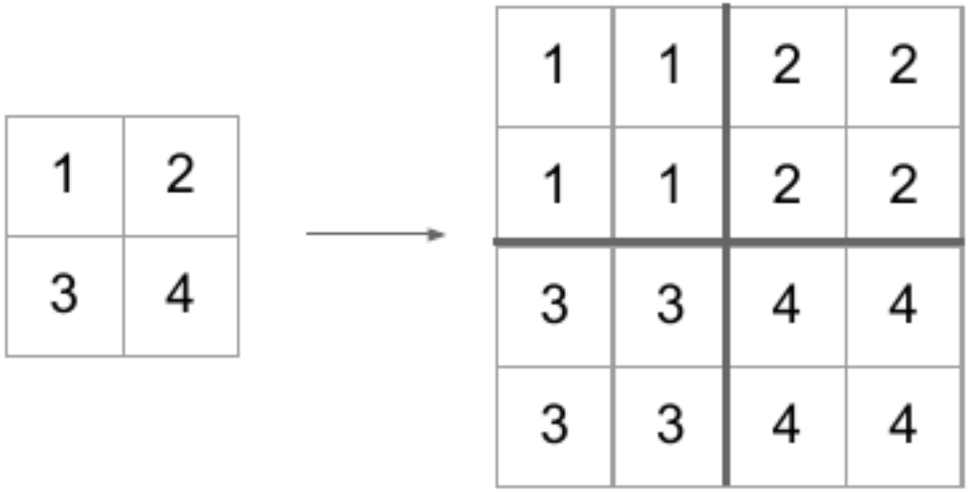
DeconvNet
Up-sampling Convolutions or ”Deconvolutions”

- Backbone: VGG



http://cvlab.postech.ac.kr/research/deconvnet/

Unpooling

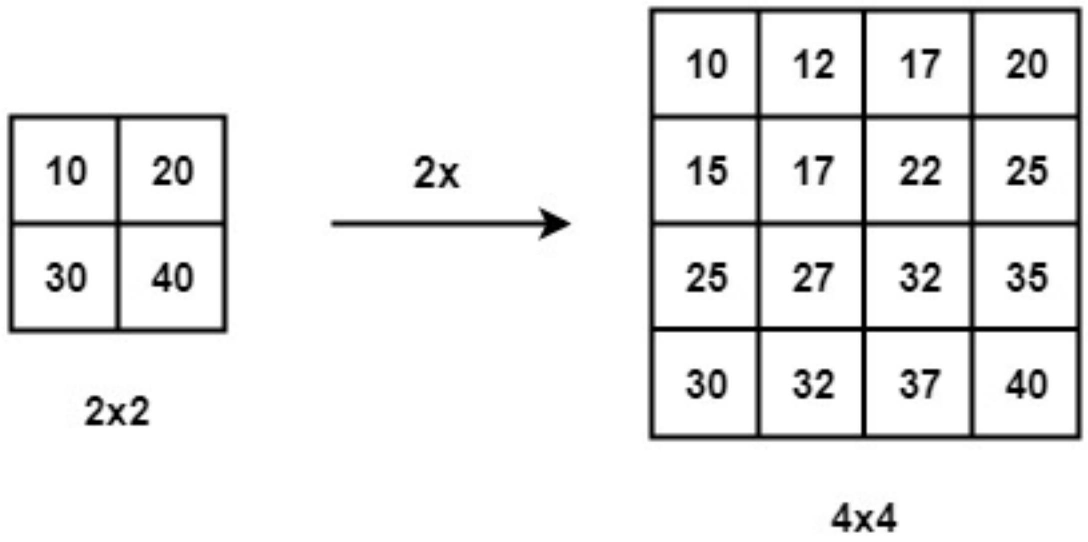


Input: 2 x 2

Output: 4 x 4

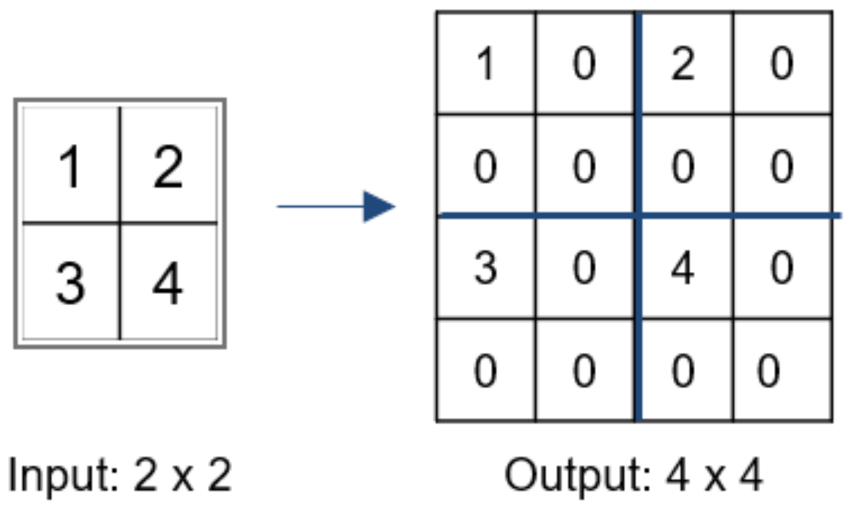
Unpooling

- Bilinear interpolation



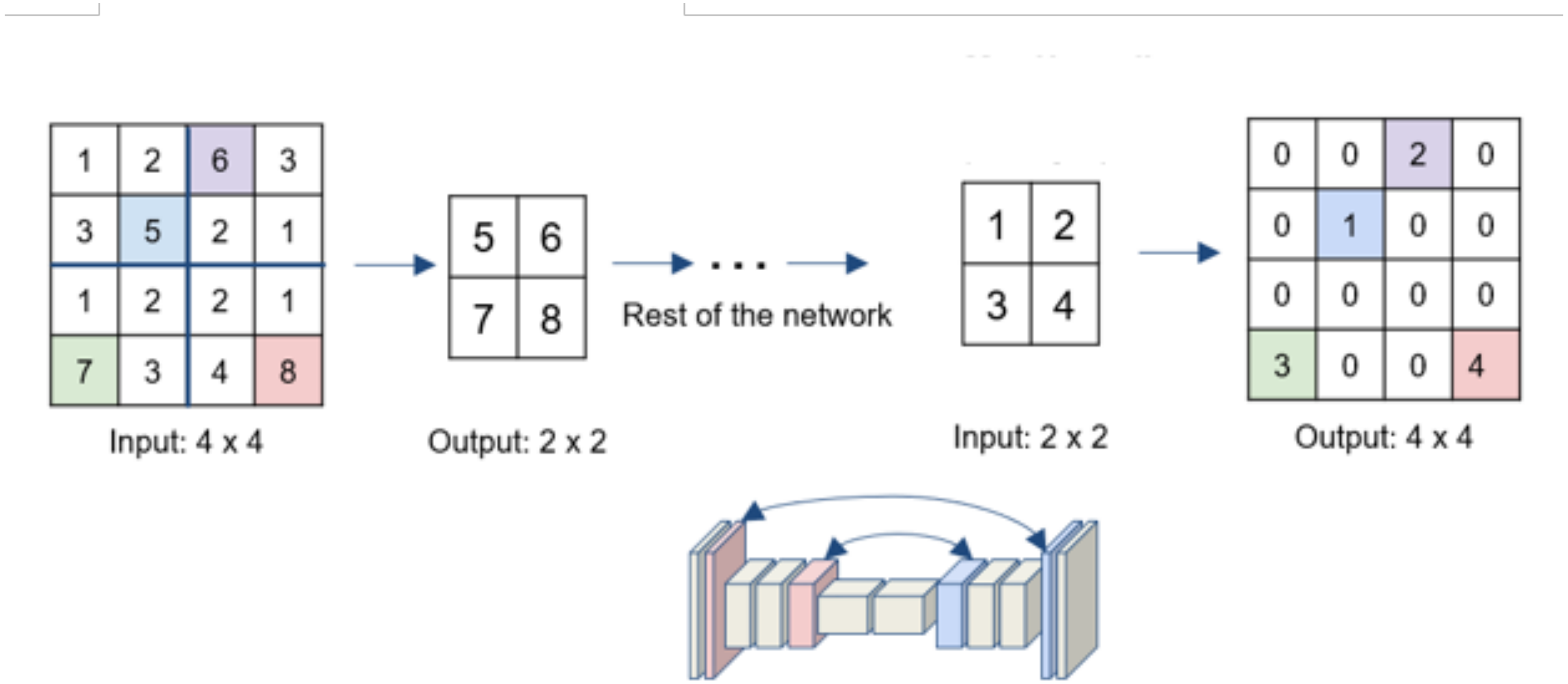
Unpooling

- Bed of nails



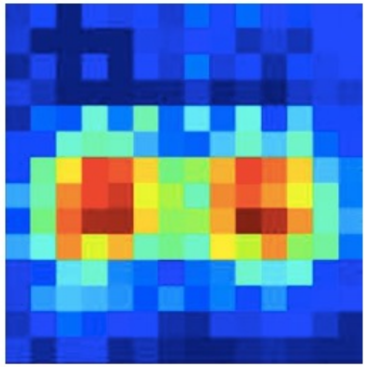
Unpooling

- Max unpooling

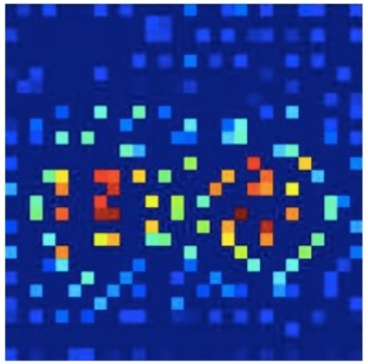


DeconvNet

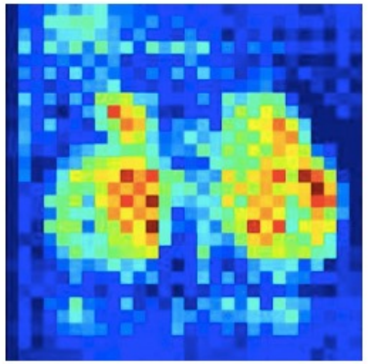
Original image



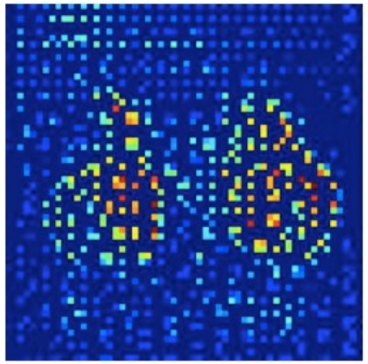
14x14 deconv



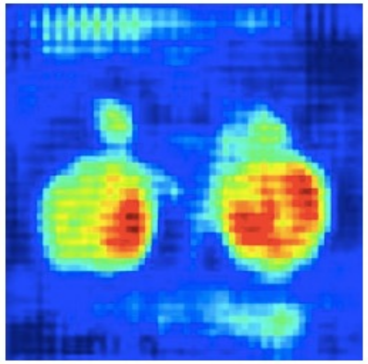
28x28 unpooling



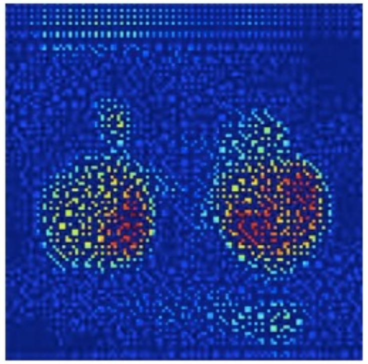
28x28 deconv



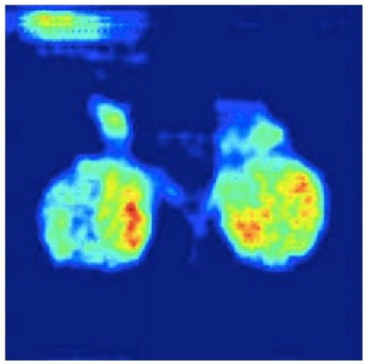
54x54 unpooling



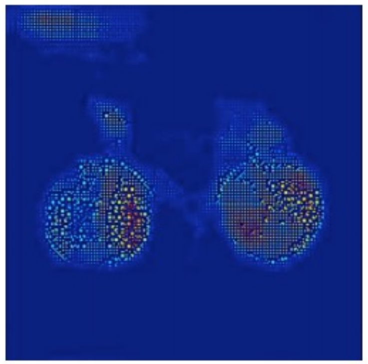
54x54 deconv



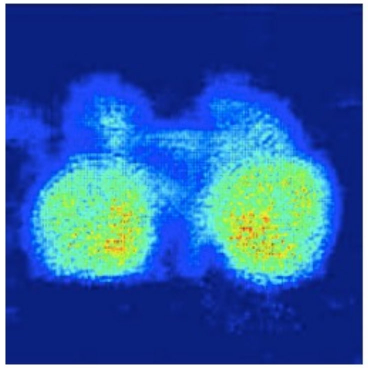
112x112 unpooling



112x112 deconv

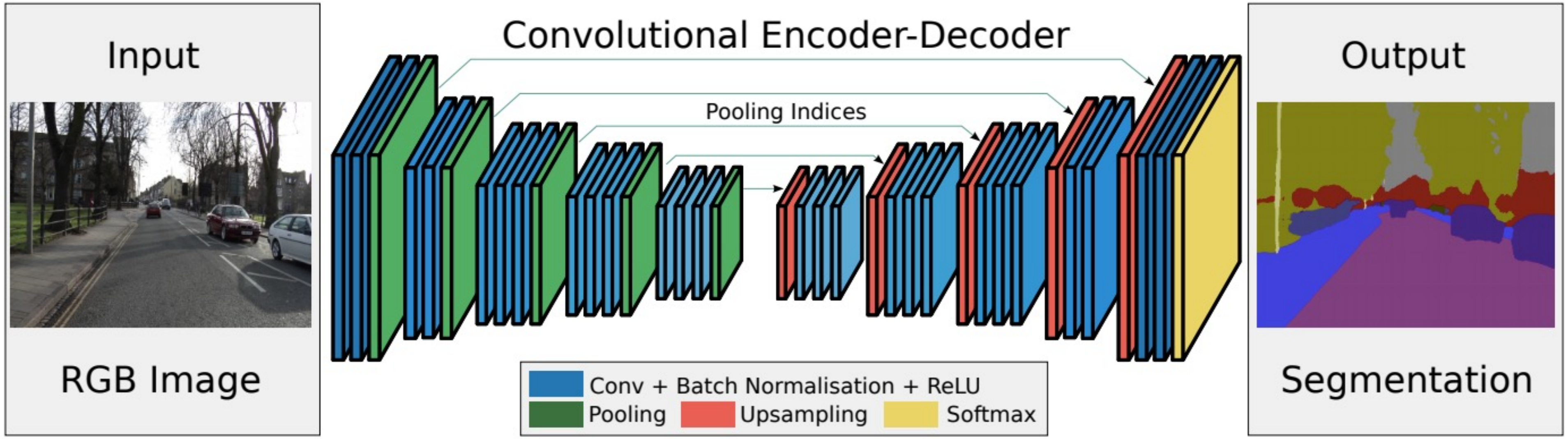


224x224 unpooling



224x224 deconv

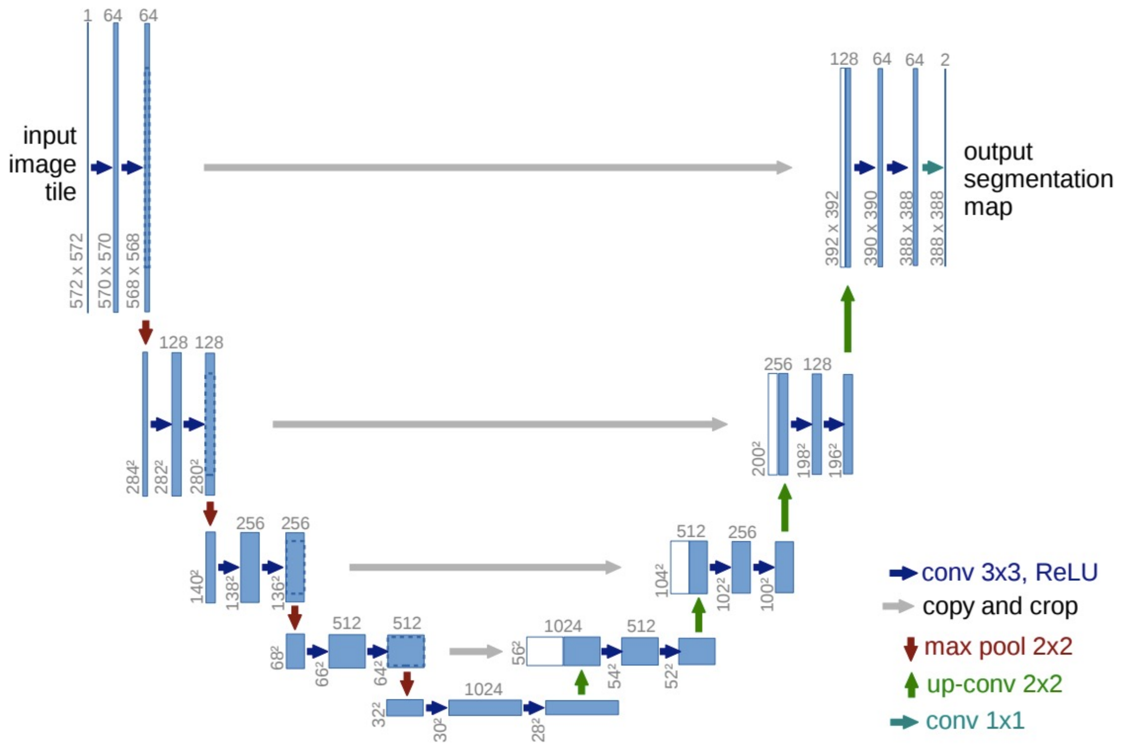
SegNet



Eliminando i FC layer, porta a risultati migliori

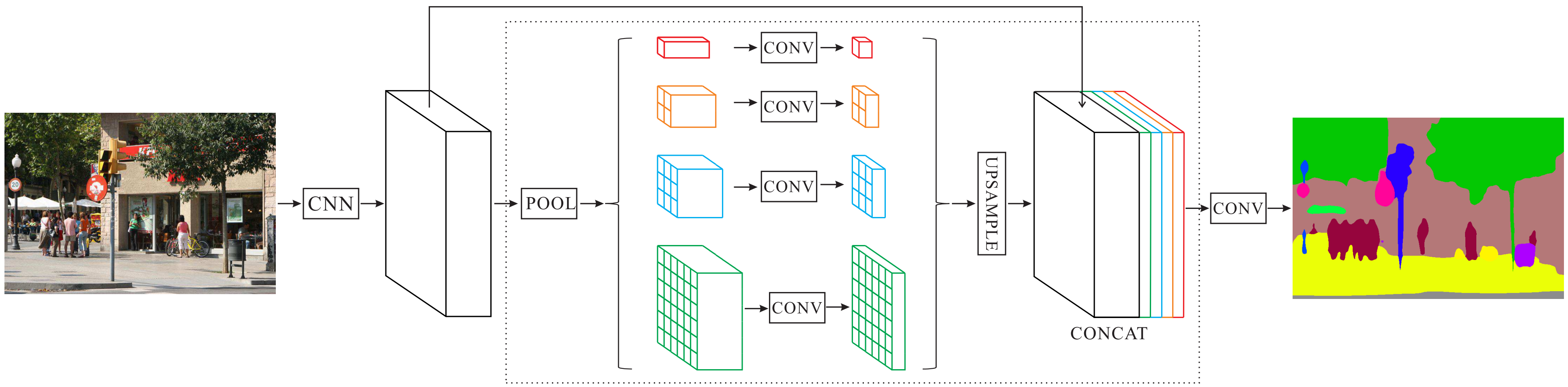
U-Net

- Usa le skip connections per combinare le feature maps
- La combinazione viene effettuata per concatenazione



Metodi Multi-scala

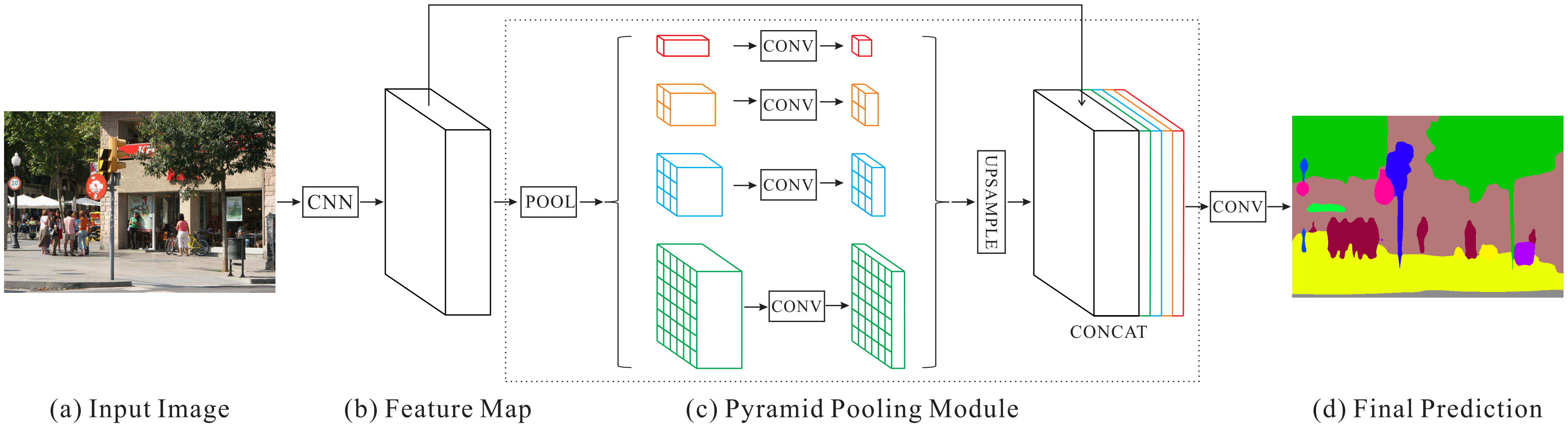
- Idea generale
  - Otteniamo una feature map utilizzando un’architettura standard (ResNet)
  - Applichiamo una serie di convoluzioni con filtri di dimensioni diverse per ottenere risoluzioni diverse
  - Encoding delle varie scale
  - Upsampling e combinazione dei risultati



(a) Input Image (b) Feature Map (c) Pyramid Pooling Module (d) Final Prediction

Metodi Multi-scala

- Esplosione combinatoria del numero di parametri

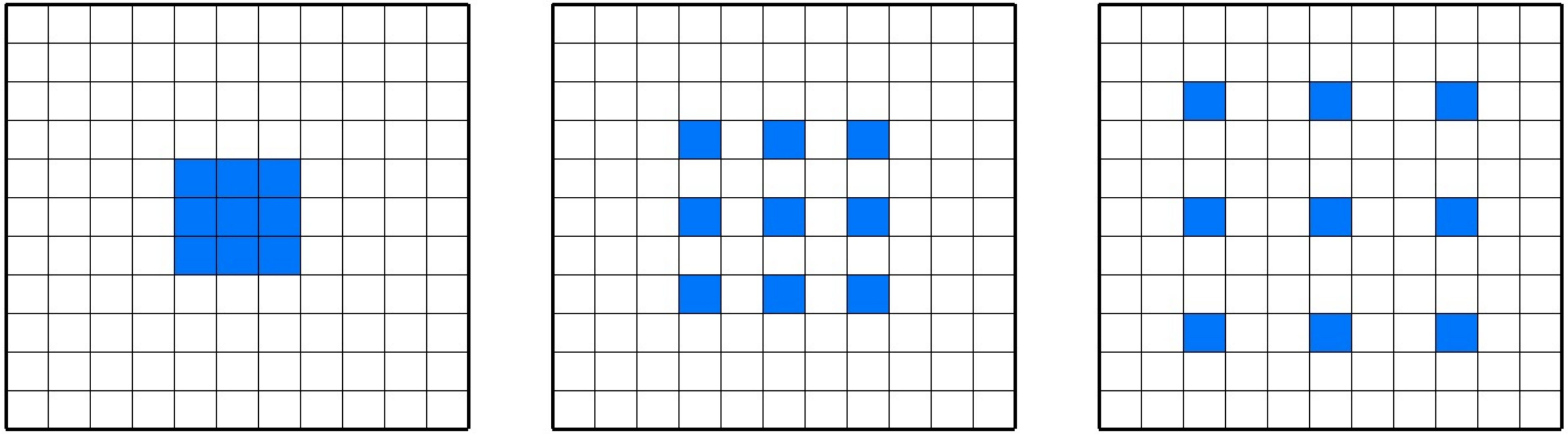


- Soluzione: Dilated convolutions

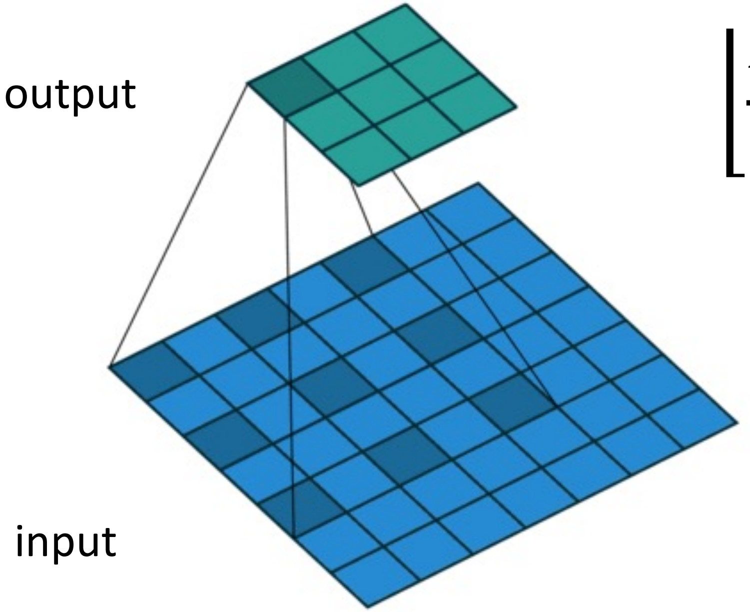
Dilated convolutions

- Invece di ridurre la risoluzione spaziale delle feature maps, utilizziamo un filtro sparso

Dilation factor 1 | Dilation factor 2 | Dilation factor 3

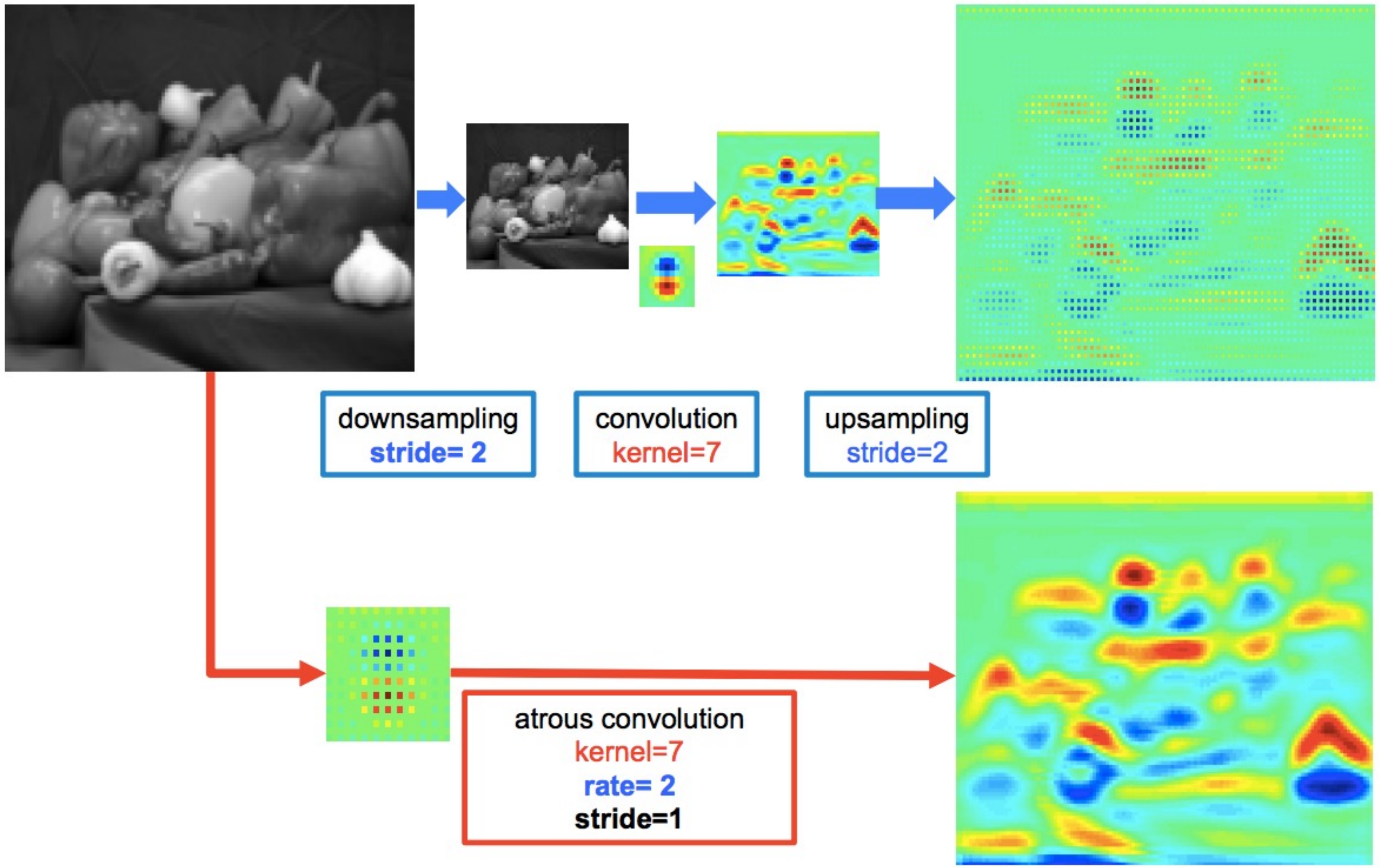


Dilated convolutions



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

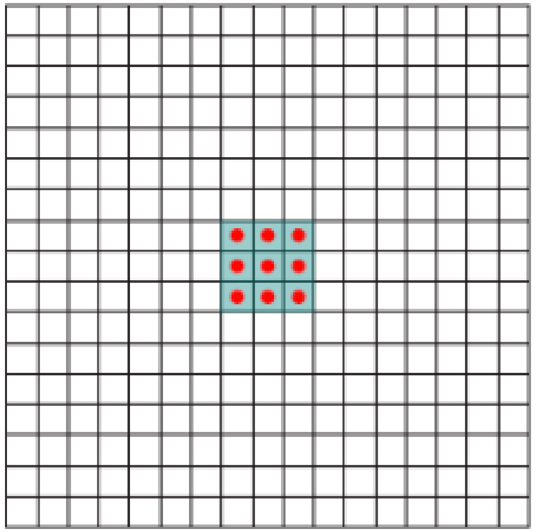
Dilated convolutions



Dilated convolutions

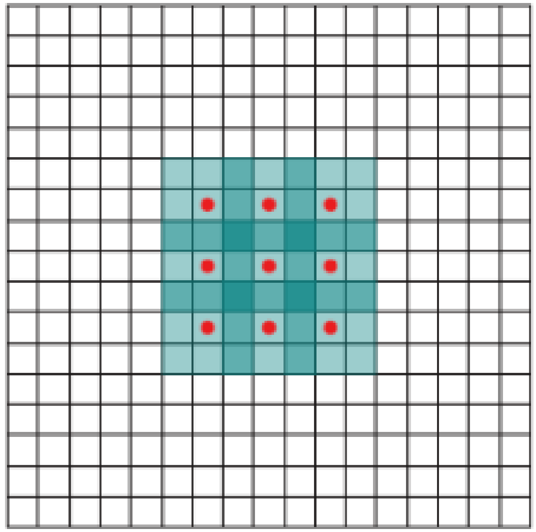
- La dimensione del receptive field cresce esponenzialmente ma il numero di parametri è lineare

F1 calcolata da F0 con 1-dilated convolution



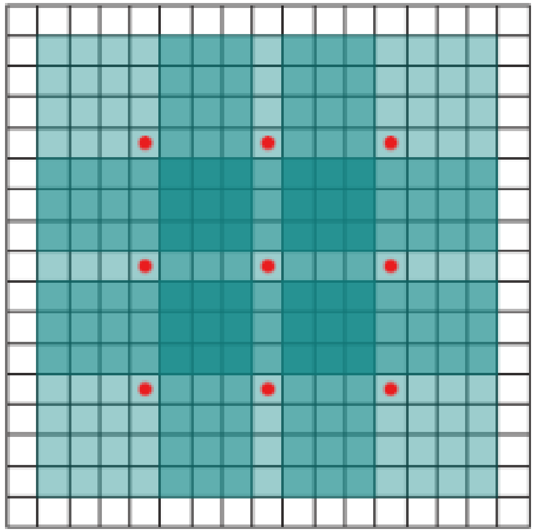
Receptive field: 3x3

F2 calcolata da F1 con 2-dilated convolution



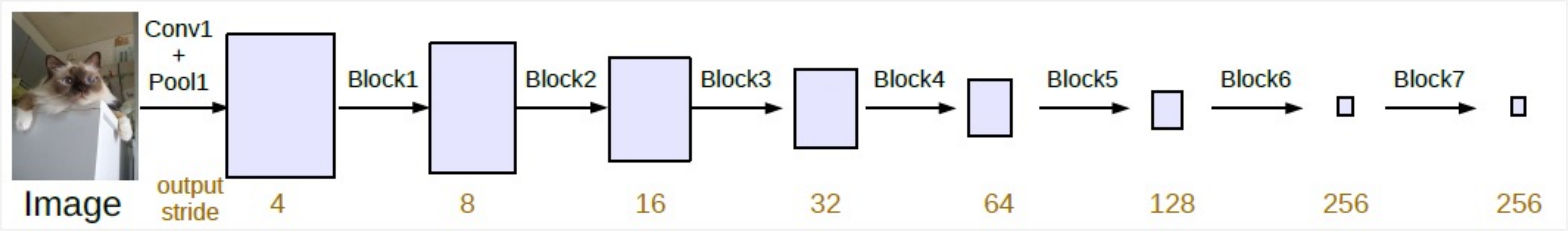
Receptive field: 7x7

F3 calcolata da F2 4-dilated convolution

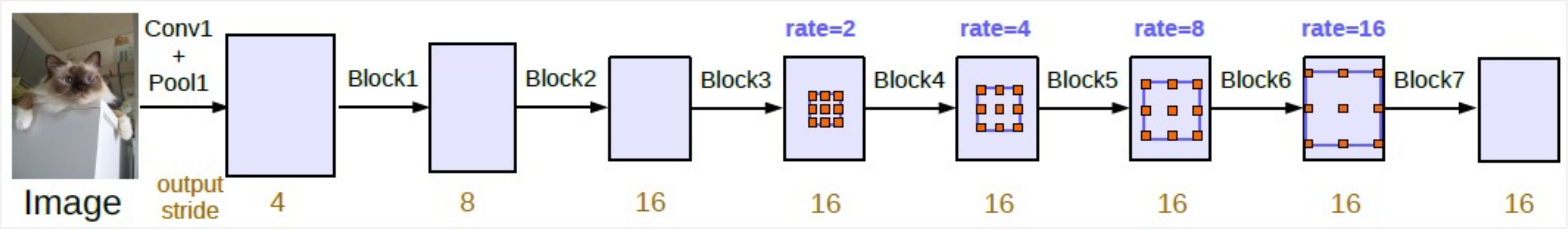


Receptive field: 15x15

Vantaggi

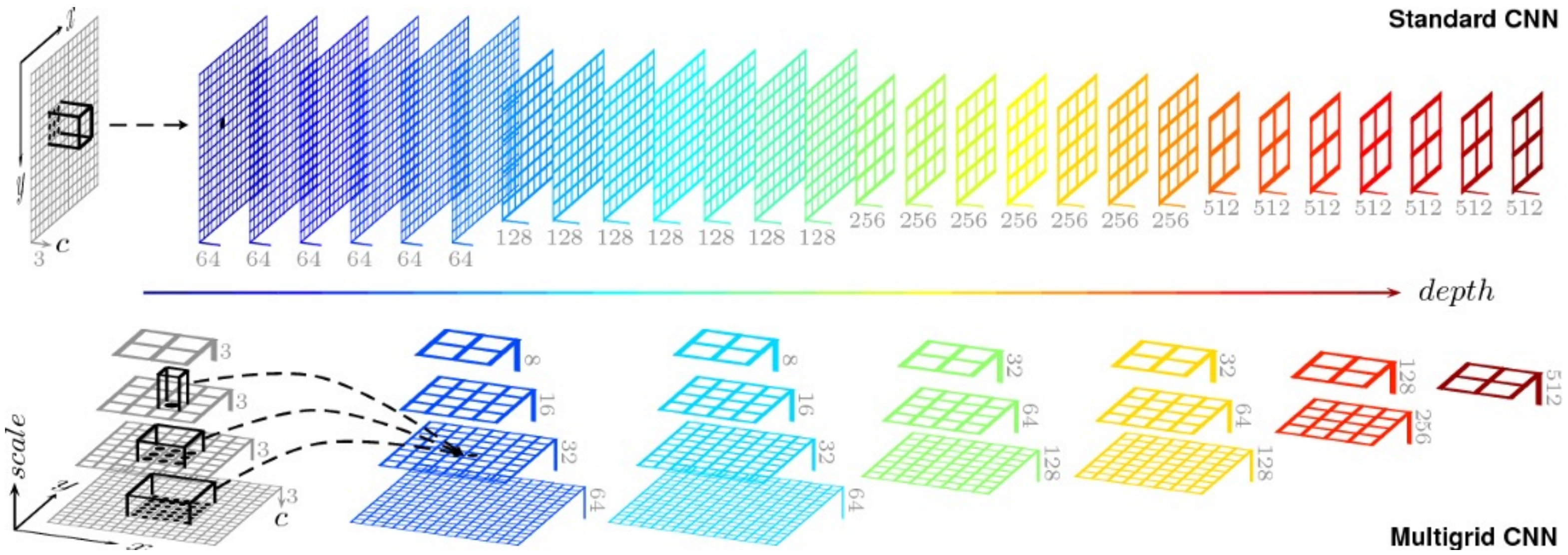


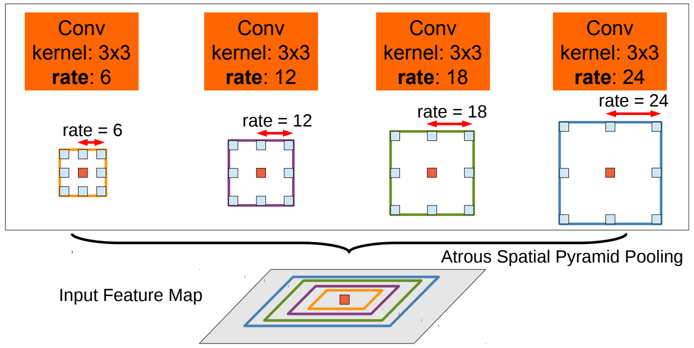
(a) Going deeper without atrous convolution.



(b) Going deeper with atrous convolution. Atrous convolution with $rate > 1$ is applied after block3 when $output\_stride = 16$.

Multigrid CNN



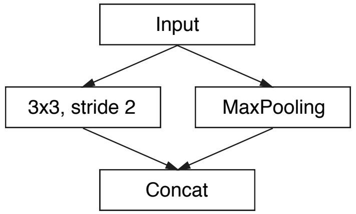


Real-Time Semantic Segmentation

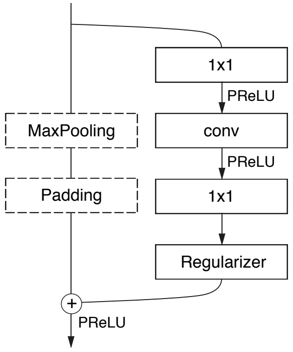
- ENet
- ICNet
- Fast-SCNN
- DFANet
- …

ENet

- Combina Encoder-Decoder con blocchi ResNet-like
  - 5 stadi
  - Sfrutta la riduzione e successivo restore dei canali per migliorare l'efficienza
- Design choices per l'efficienza
  - Early downsampling
    - I primi due blocchi riducono la size in maniera significativa
  - Ricostruzione tramite MaxUnpooling
  - Decoder size
    - Large encoder, small decoder
  - Non-linear activations
    - PReLU invece delle ReLU
  - Asymmetric convolutions, dilated convolutions
  - Regularization
    - Stochastic Depth, spatial dropout



Initial Block



Bottleneck prototype

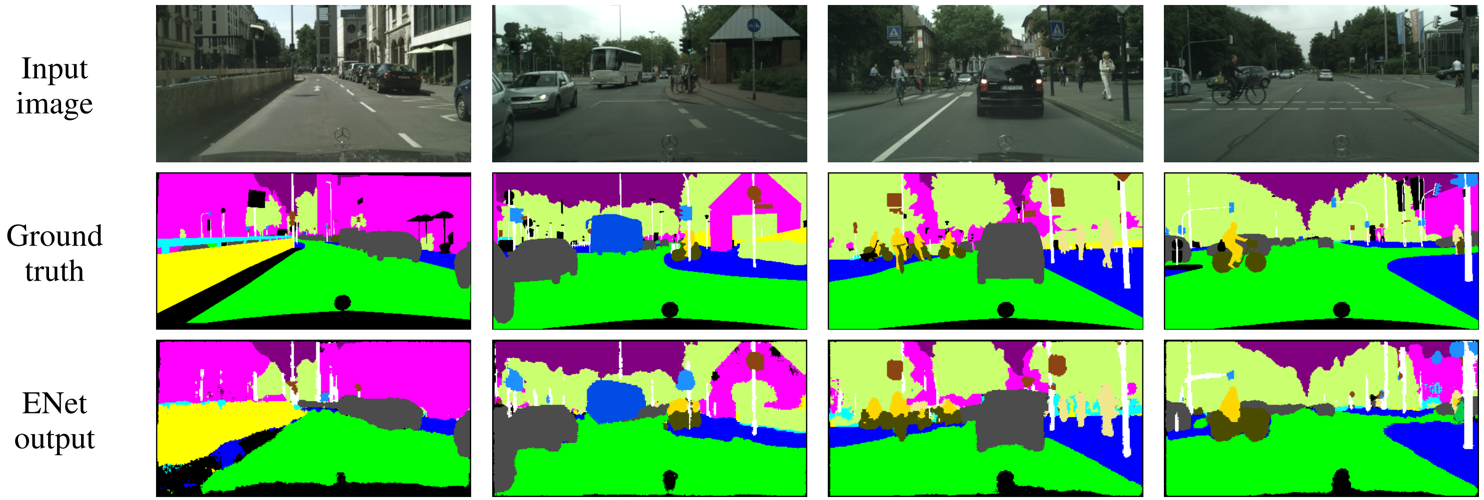
Table 1: ENet architecture. Output sizes are given for an example input of 512×512.

Name	Type	Output size
initial		$16 \times 256 \times 256$
bottleneck1.0	downsampling	$64 \times 128 \times 128$
$4\times$ bottleneck1.x		$64 \times 128 \times 128$
bottleneck2.0	downsampling	$128 \times 64 \times 64$
bottleneck2.1		$128 \times 64 \times 64$
bottleneck2.2	dilated 2	$128 \times 64 \times 64$
bottleneck2.3	asymmetric 5	$128 \times 64 \times 64$
bottleneck2.4	dilated 4	$128 \times 64 \times 64$
bottleneck2.5		$128 \times 64 \times 64$
bottleneck2.6	dilated 8	$128 \times 64 \times 64$
bottleneck2.7	asymmetric 5	$128 \times 64 \times 64$
bottleneck2.8	dilated 16	$128 \times 64 \times 64$
Repeat section 2, without bottleneck2.0		
bottleneck4.0	upsampling	$64 \times 128 \times 128$
bottleneck4.1		$64 \times 128 \times 128$
bottleneck4.2		$64 \times 128 \times 128$
bottleneck5.0	upsampling	$16 \times 256 \times 256$
bottleneck5.1		$16 \times 256 \times 256$
fullconv		$C \times 512 \times 512$

ENet

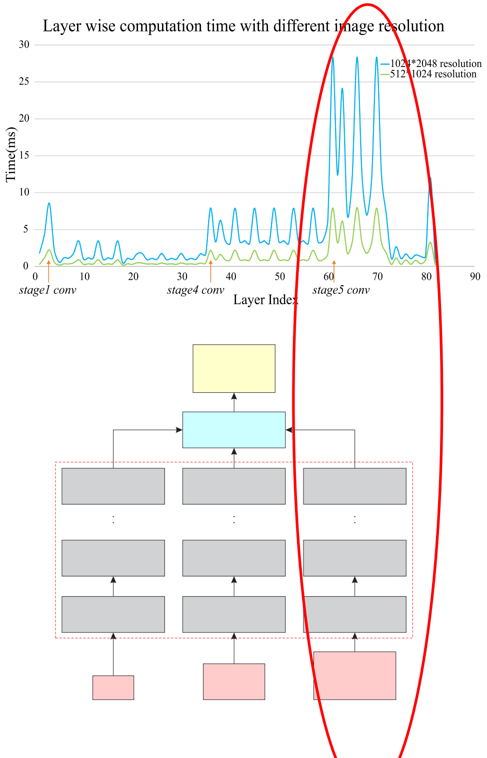
Model	NVIDIA TX1						NVIDIA Titan X					
	480×320		640×360		1280×720		640×360		1280×720		1920×1080	
	ms	fps	ms	fps	ms	fps	ms	fps	ms	fps	ms	fps
SegNet	757	1.3	1251	0.8	-	-	69	14.6	289	3.5	637	1.6
ENet	47	21.1	69	14.6	262	3.8	7	135.4	21	46.8	46	21.6

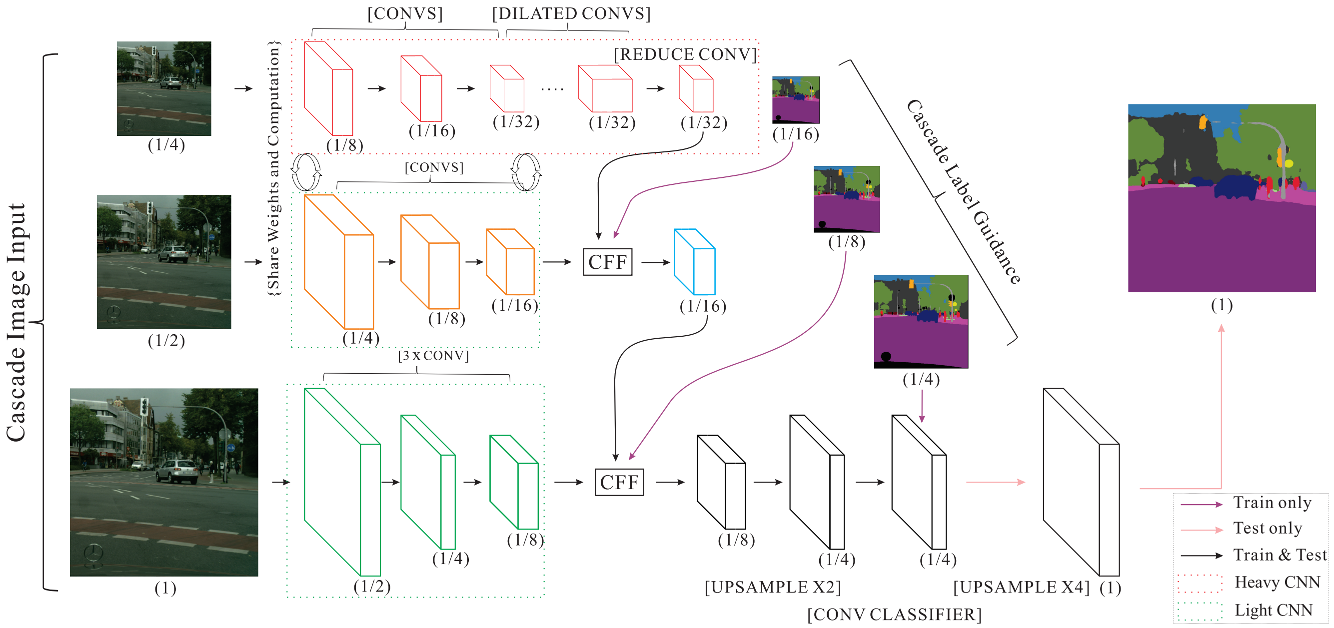
Model	Class IoU	Class iIoU	Category IoU	Category iIoU
SegNet	56.1	34.2	79.8	**66.4**
ENet	**58.3**	**34.4**	**80.4**	64.0



ICNet

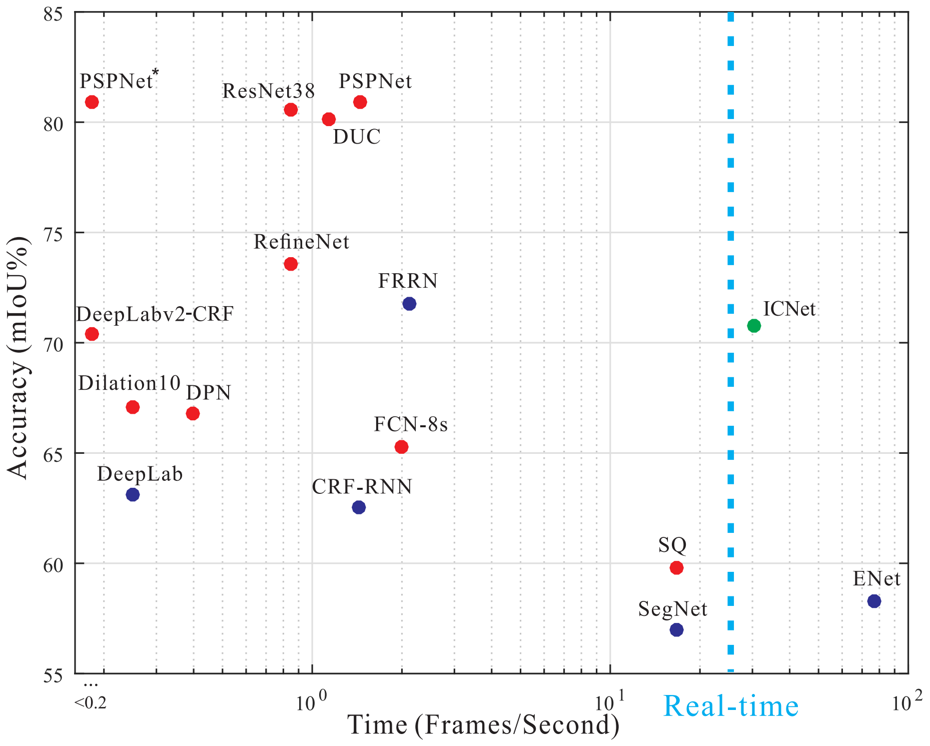
- Analisi dei bottleneck nei metodi multi-scala
  - La convoluzione su immagini grandi è costosa
  - Soluzione: combinazione «furba» per accellerare la computazione





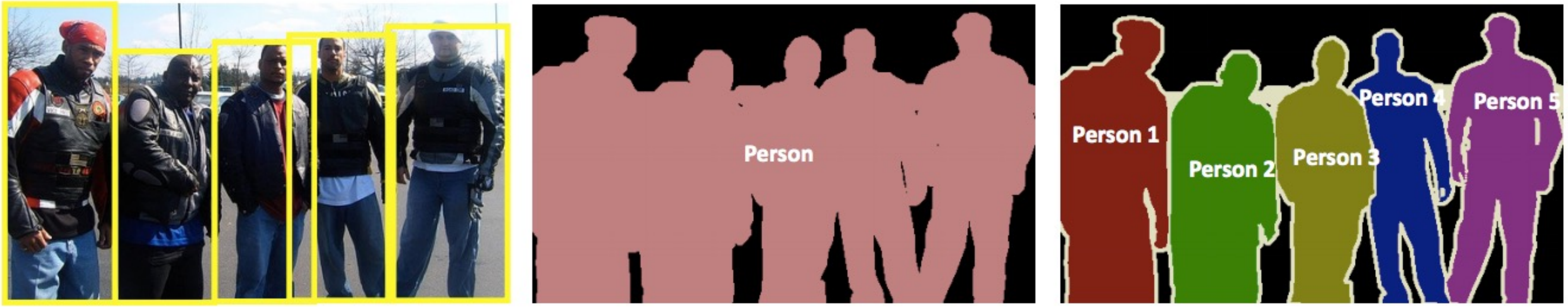
ICNet

- Trade-off tra velocità e accuratezza



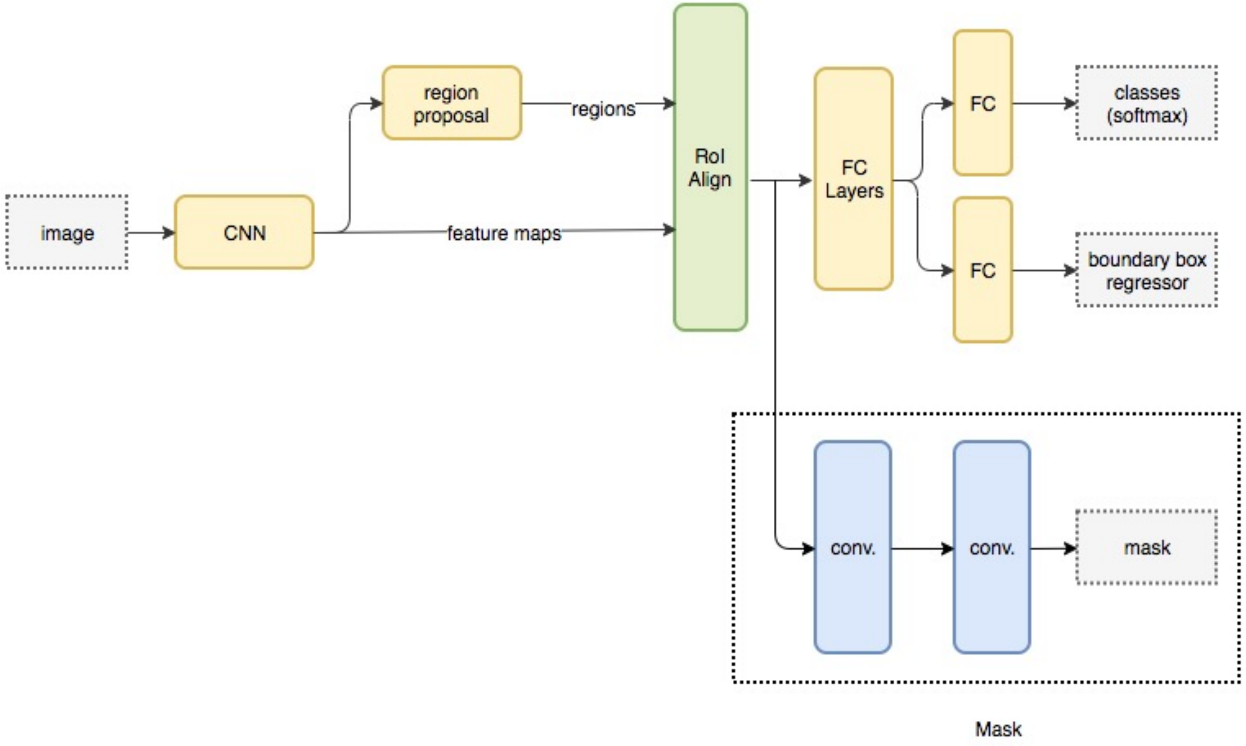
Instance Segmentation

- Obiettivo
  - Individuare non solo la segmentazione, ma anche l'istanza



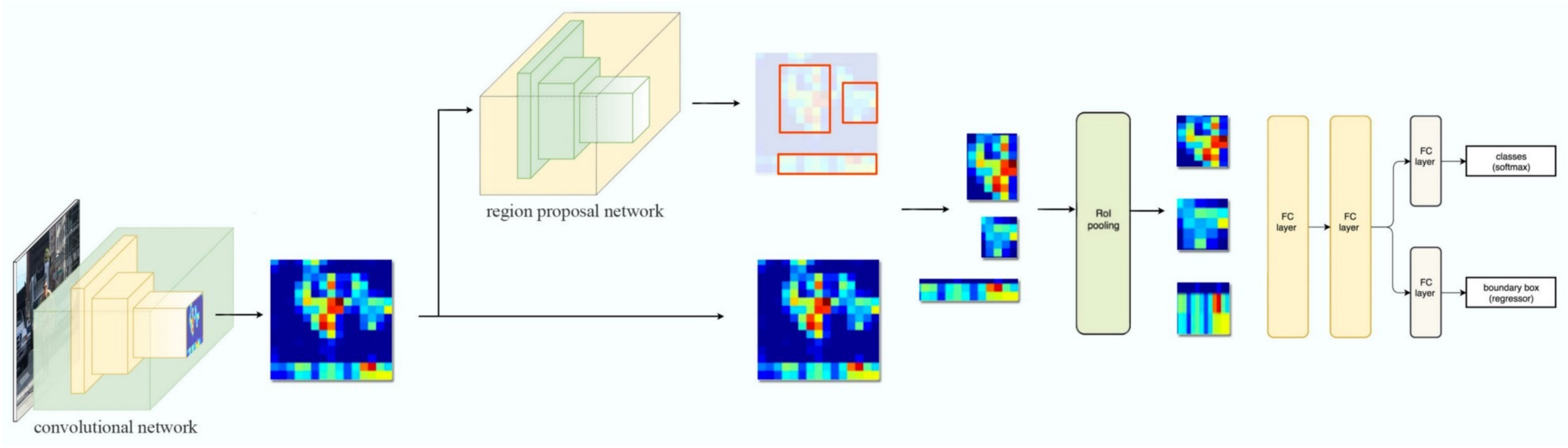
Mask R-CNN

- Mask R-CNN = Faster R-CNN + FCN sui RoIs

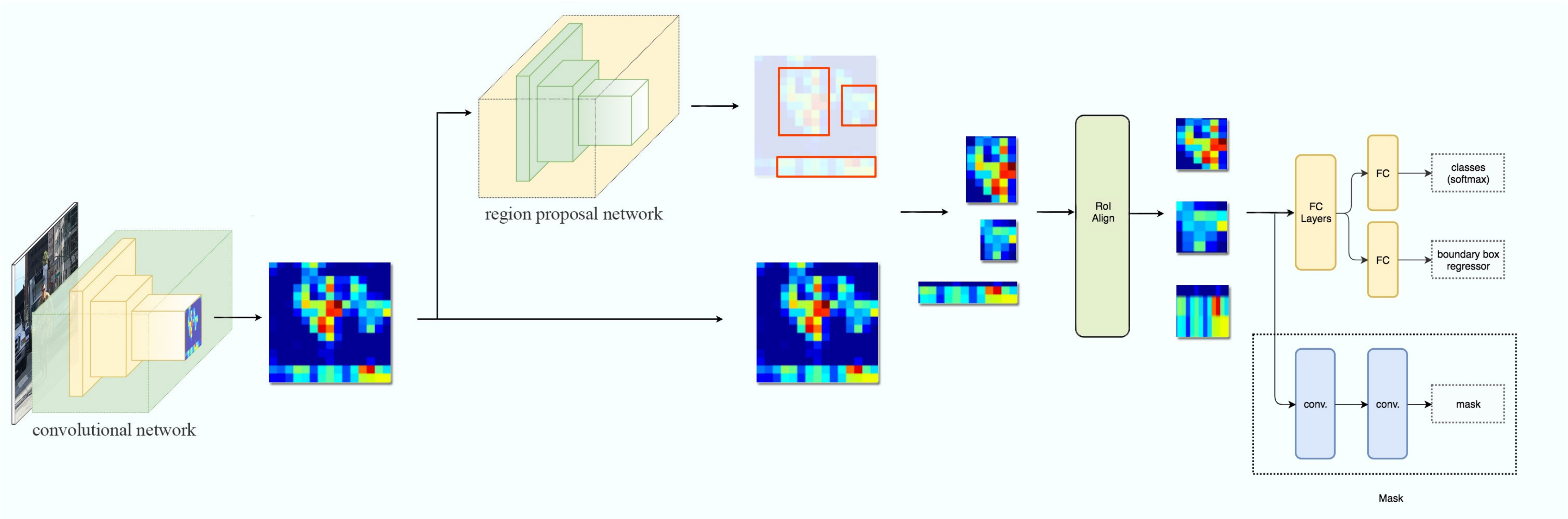


Loss: $L_{cs} + L_{box} + L_{mask}$

Recap: Faster R-CNN

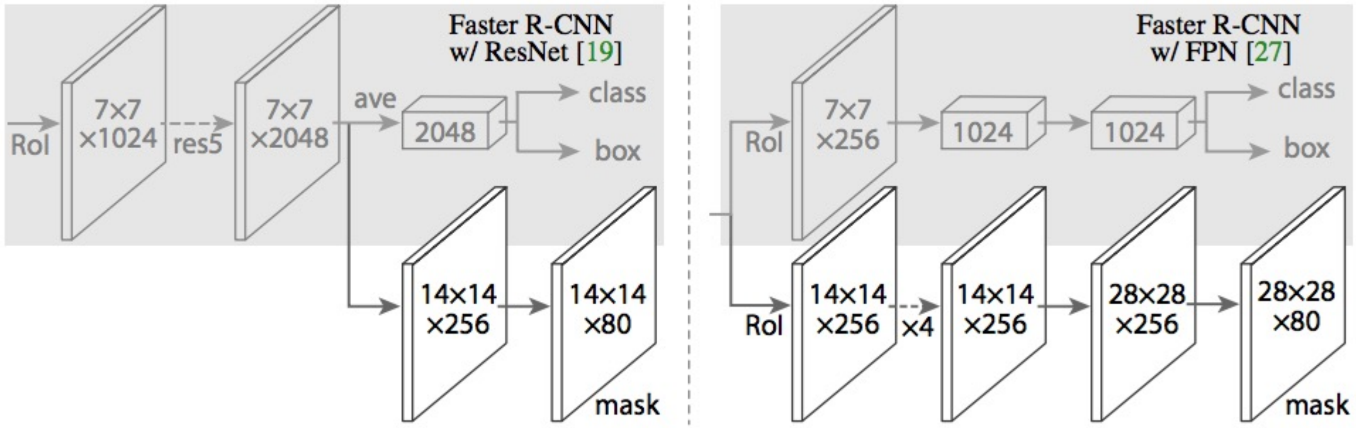


Da Faster R-CNN a Mask R-CNN



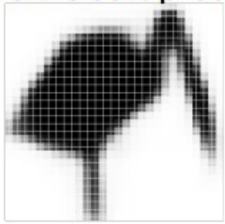
Mask R-CNN: Mask

- $K \cdot m{\times}m$
  - Una maschera di dimensione $m{\times}m$ per ognuna delle K classi
  - Ogni pixel è regolato da una sigmoide
  - Loss
    - Su una RoI associata alla classe k, L_{mask}è la binary cross-entropy relativa alla maschera m_k associata
      - Le altre maschere non contribuiscono alla loss



Mask R-CNN

28x28 soft prediction

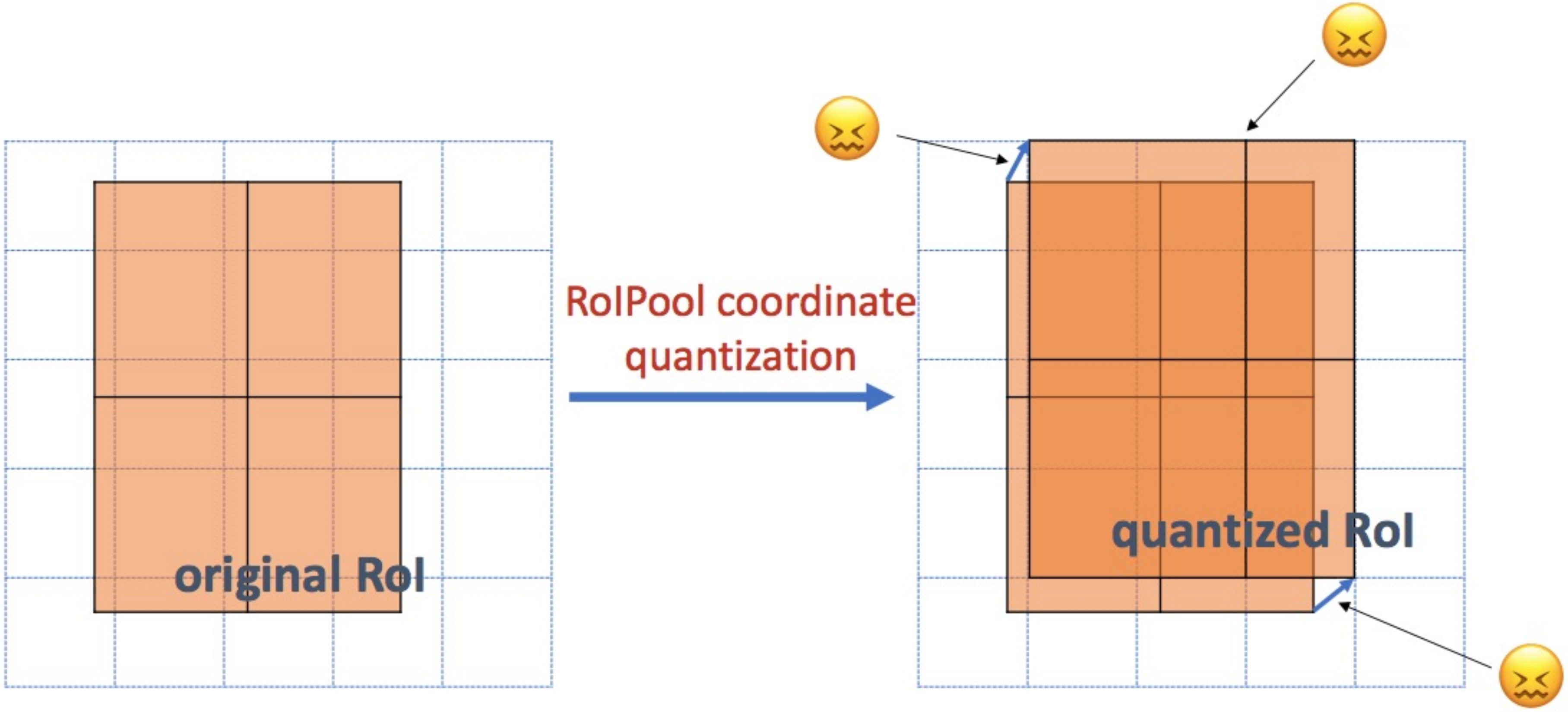


Resized Soft prediction

Final mask

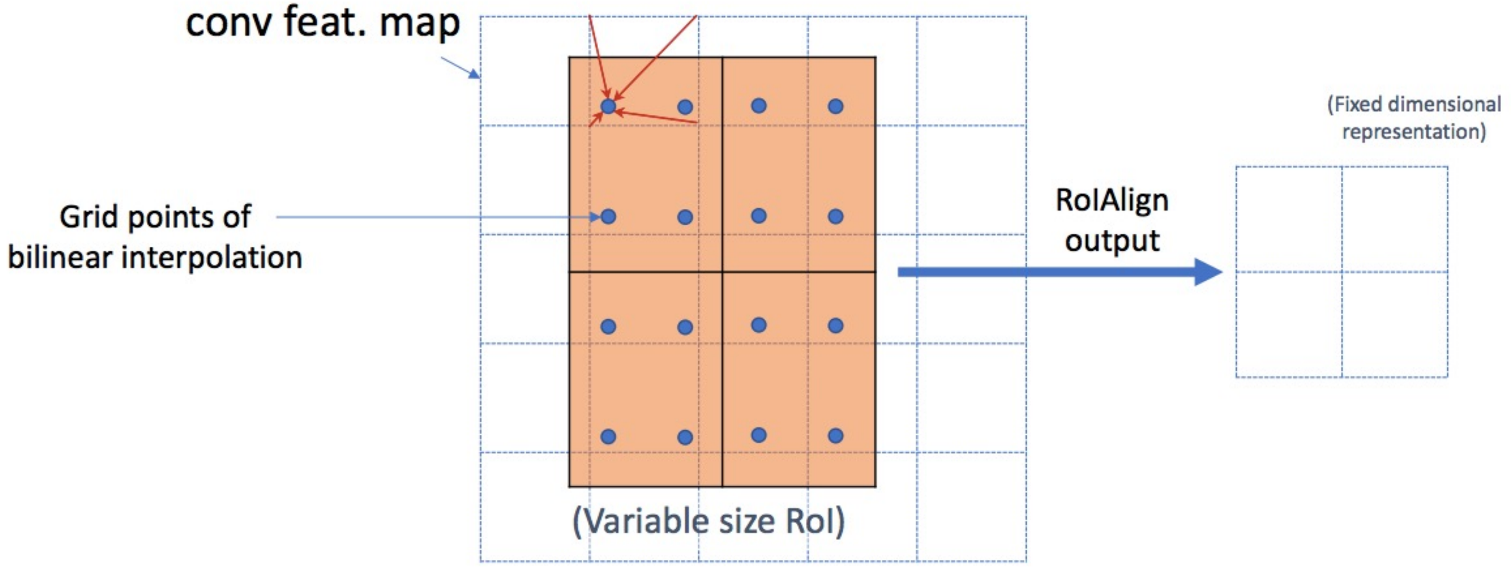
RoIAlign

- Il mapping di una regione sulla feature map con RoIPooling causa un riallineamento



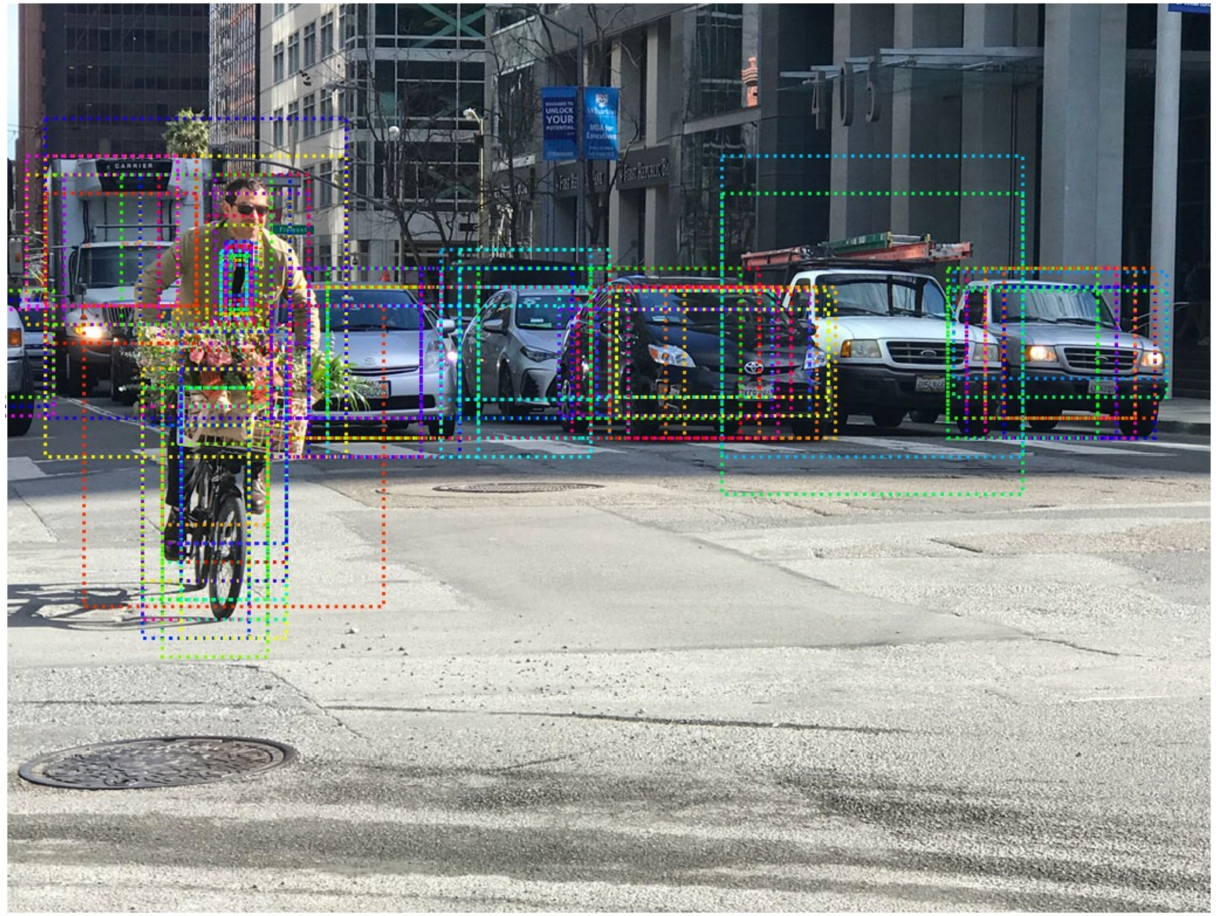
RoIAlign

- Con RoIAlign, ogni punto viene interpolato
  - Recupera precision nella ricostruzione della maschera



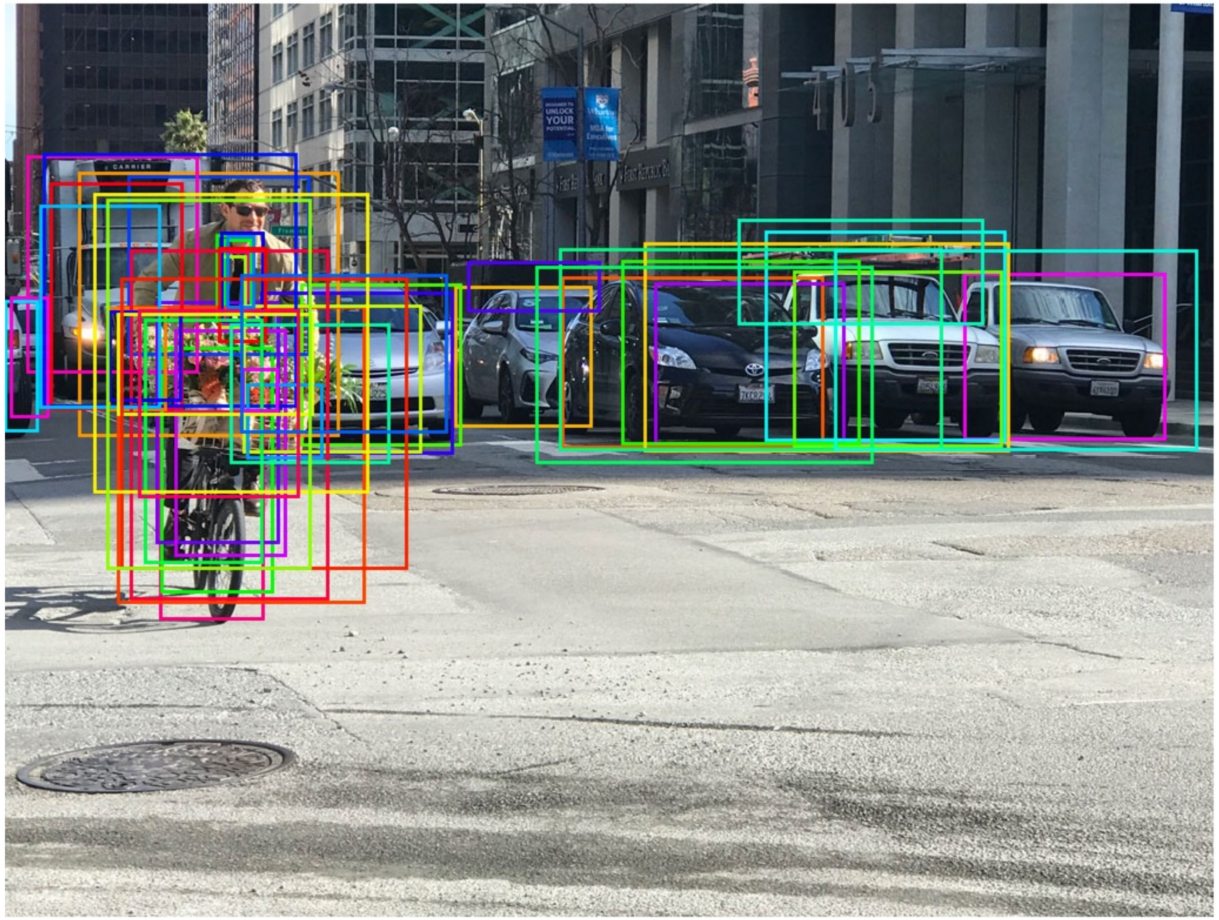
Risultati

- Priors



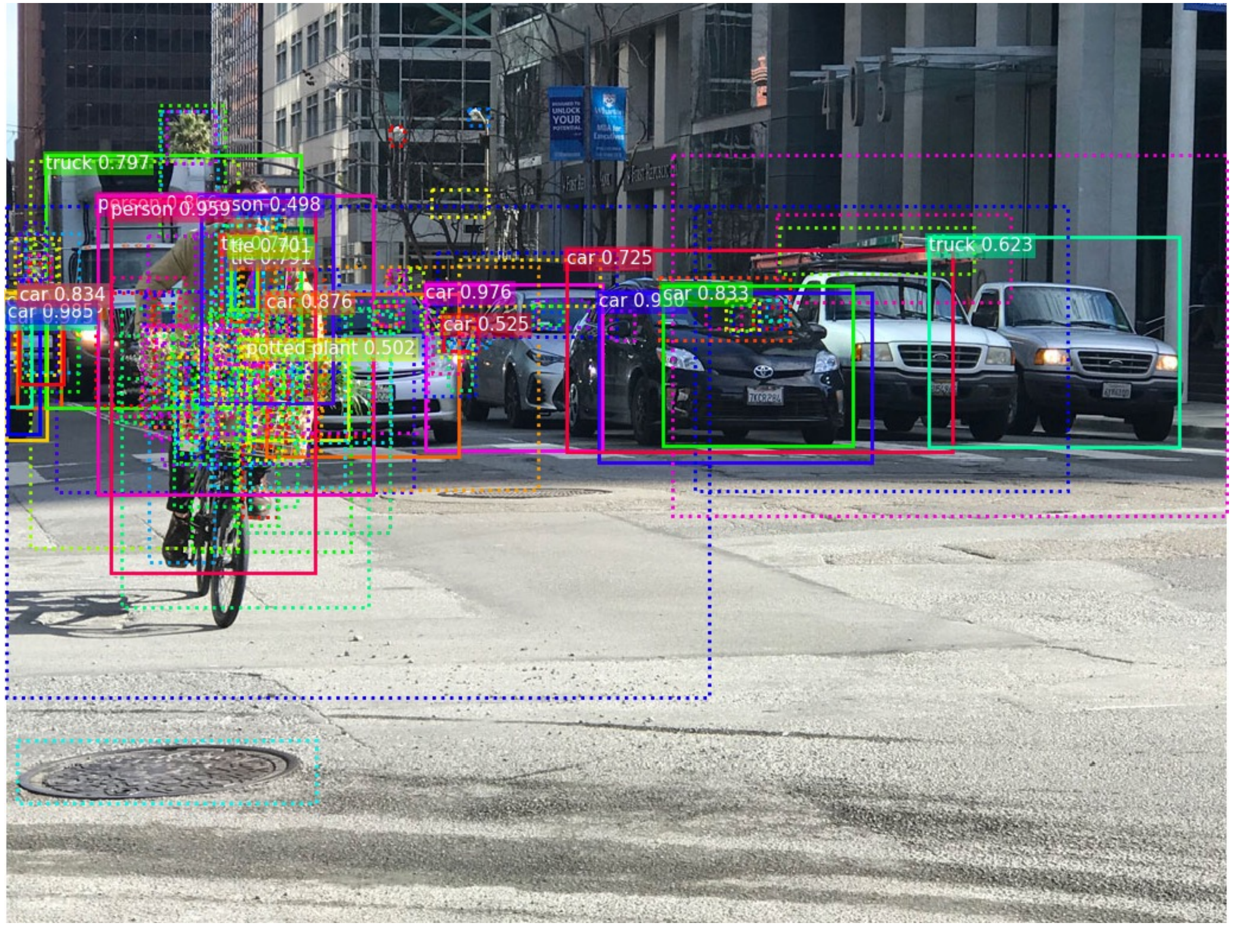
Risultati

- Region Proposals



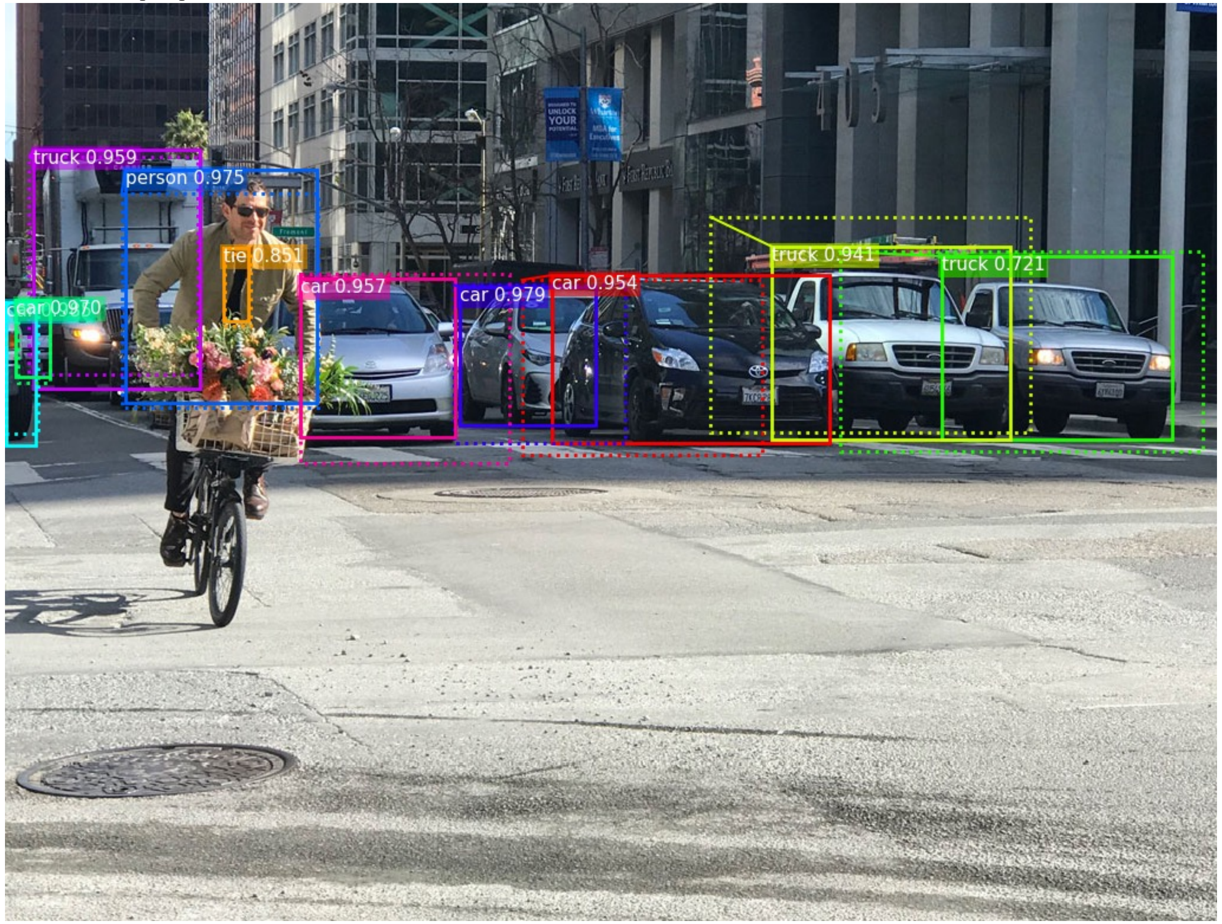
Risultati

- Predizione



Risultati

- Non-Maximum Suppression

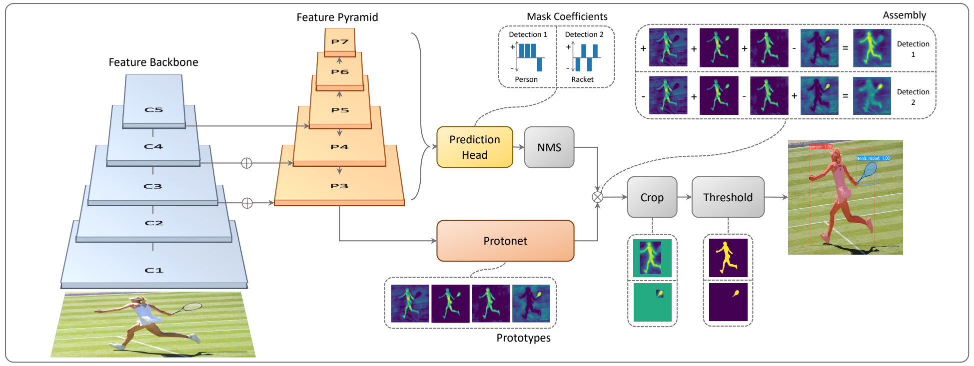


Risultati

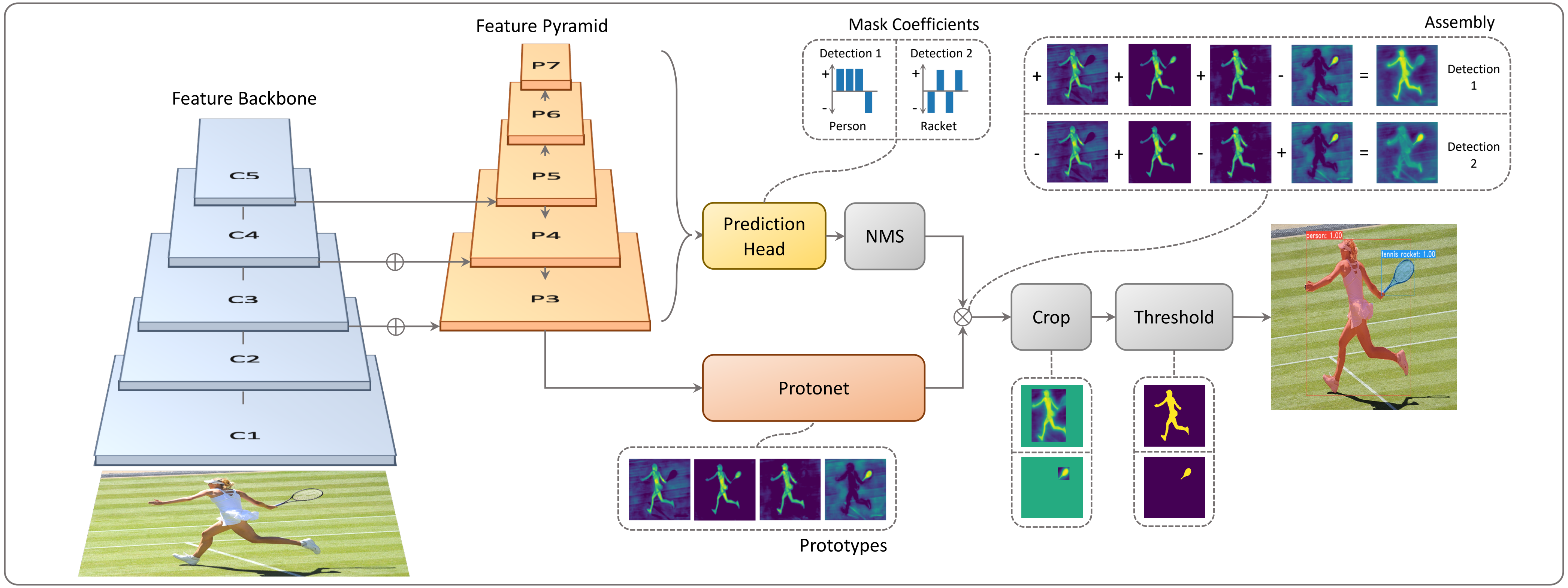
- Mask

YOLACT: You Only Look At CoefficienTs

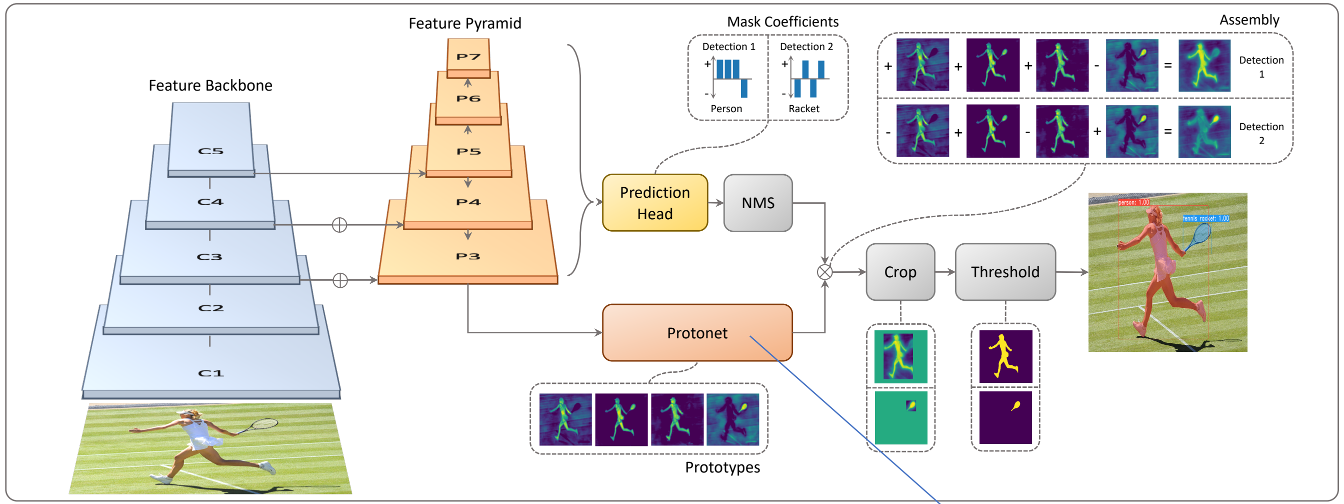
- Due task paralleli:
  - Generazione di un dizionario di non-local prototype masks sull’intera immagine
    - Basato su FCN
  - Predizione di un insieme di coefficienti di combinazione per ogni istanza
    - Aggiunge una componente all’object detection per predire un vettore di “mask coefficients”
  - Per ogni istanza selezionata nel NMS viene costruita una maschera combinando i risultati dei due task.

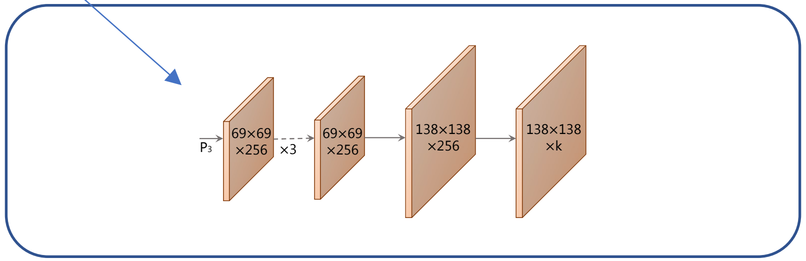


Architettura



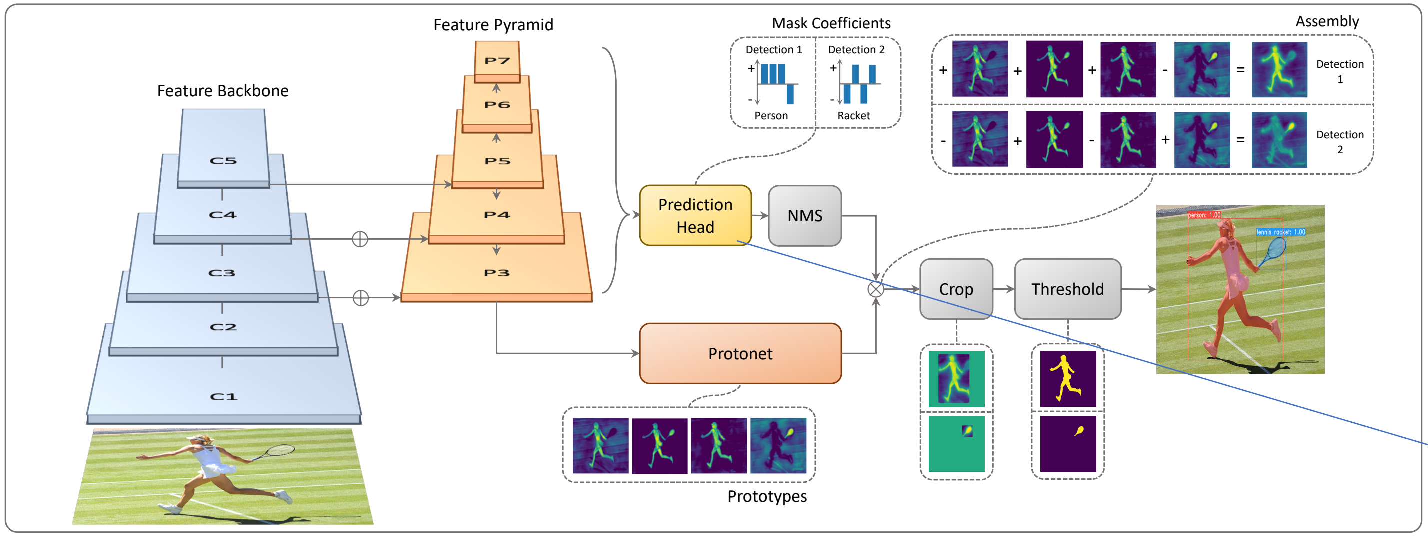
Architettura

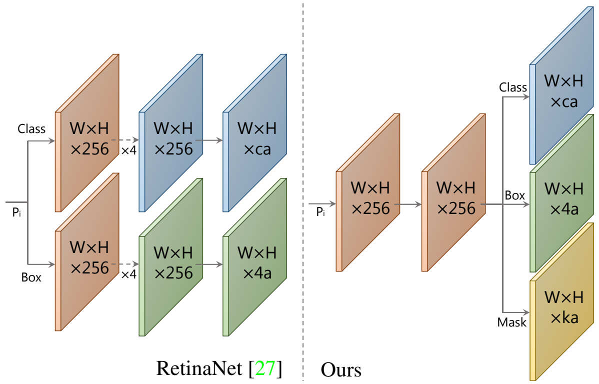




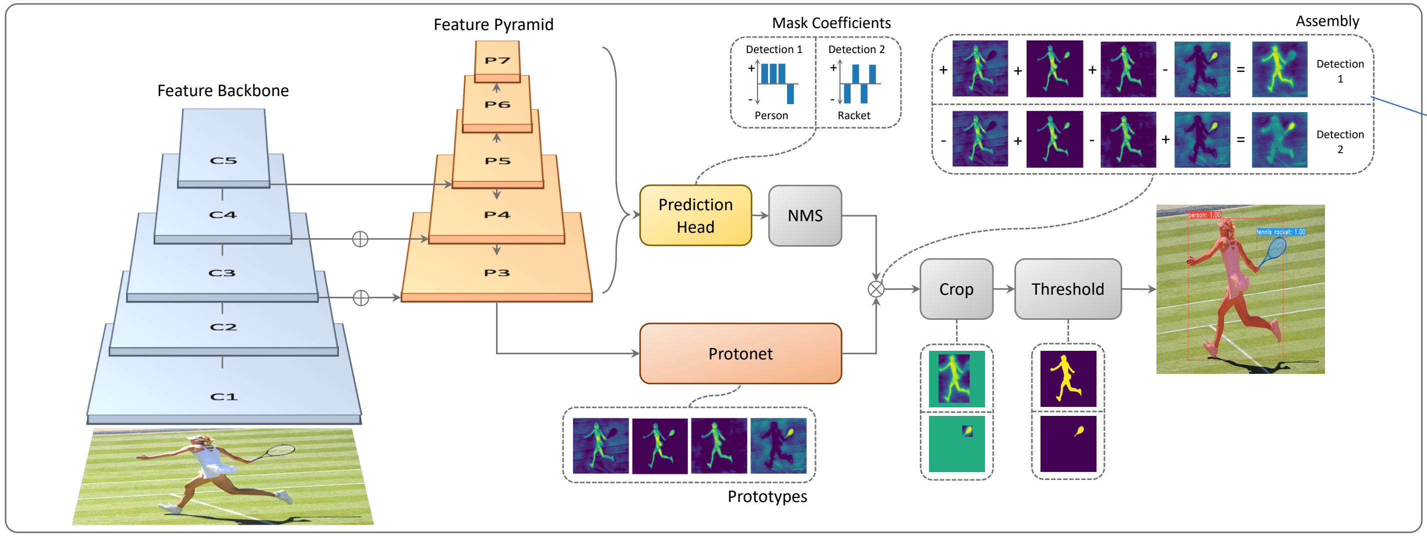
Prototype FCN

Architettura





Architettura

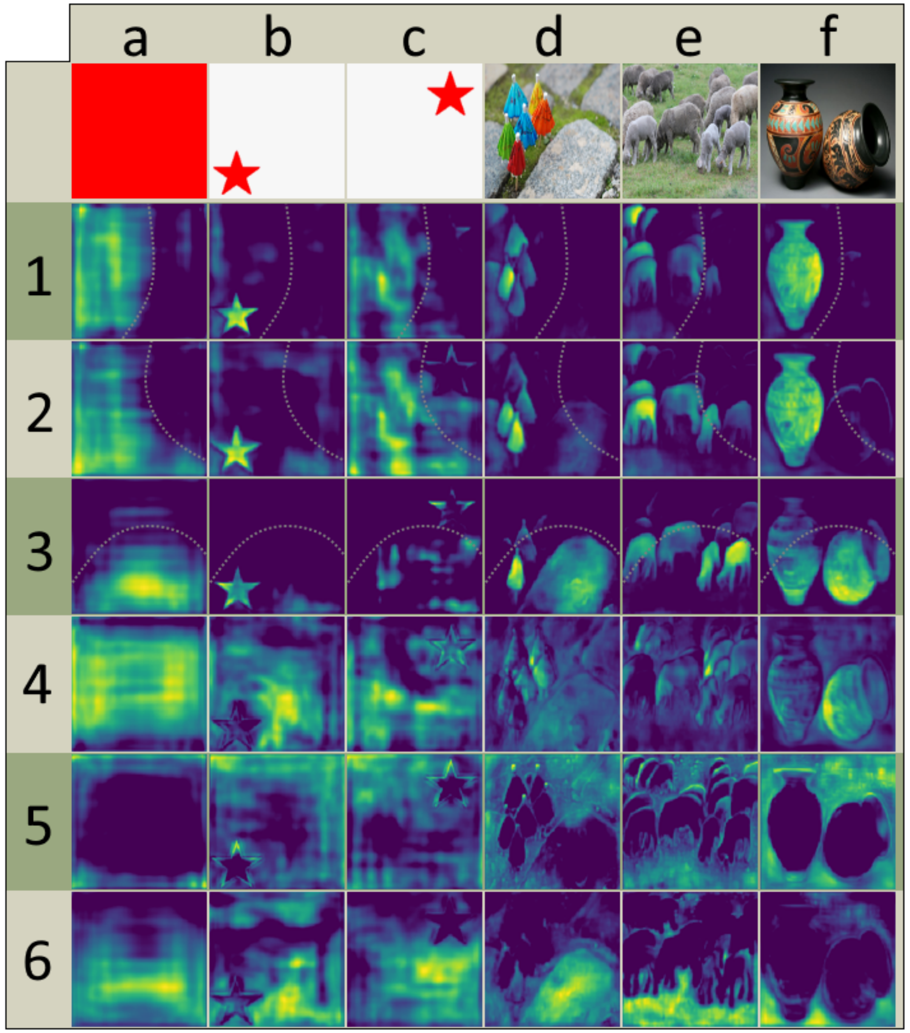


$$M = \sigma(P \cdot C^T)$$

- P matrice di maschere
- C vettore di coefficienti

Caratteristiche

- Loss
  - $L_{cs} + L_{box} + L_{mask}$
  - $L_{mask} = BCE(M, M_{gt})$
- YOLACT impara a localizzare le istanze



Risultati

- 29.8mAP, 33FPS

Riassunto

- Semantic vs. Instance segmentation
- Architetture complesse
- Base per learning task simili
    - Depth estimation
    - Surface normal estimation
    - Colorization