Analisi di Immagini e Video (Computer Vision)

Giuseppe Manco

Outline

- Object Detection
- Region Proposal Networks
- Single-Shot Detection
- Yolo

Crediti

- Slides adattate da vari corsi e libri
  - Computational Visual Recognition (V. Ordonez), CS Virgina Edu
  - Computer Vision (S. Lazebnik), CS Illinois Edu
  - Mohamed Elgendy [Elg20]
  - https://github.com/sgrvinod/a-PyTorch-Tutorial-to-Object-Detection
  - https://blog.paperspace.com/how-to-implement-a-yolo-object-detector-in-pytorch/

Image Classification

dog

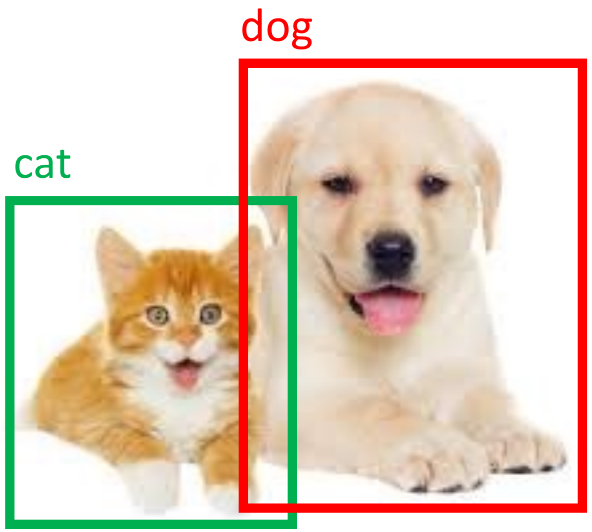
Multi-label classification

dog

dog,cat

Single-Object Detection

Multi-Object Detection



Cosa caratterizza la posizione di un oggetto?

Cosa caratterizza la posizione di un oggetto?

- Boundary coordinates
  - $(x_1, y_1), (x_2, y_2)$

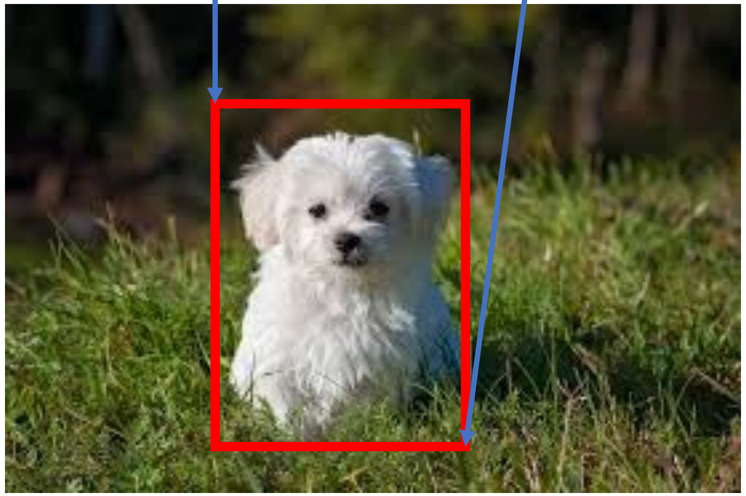
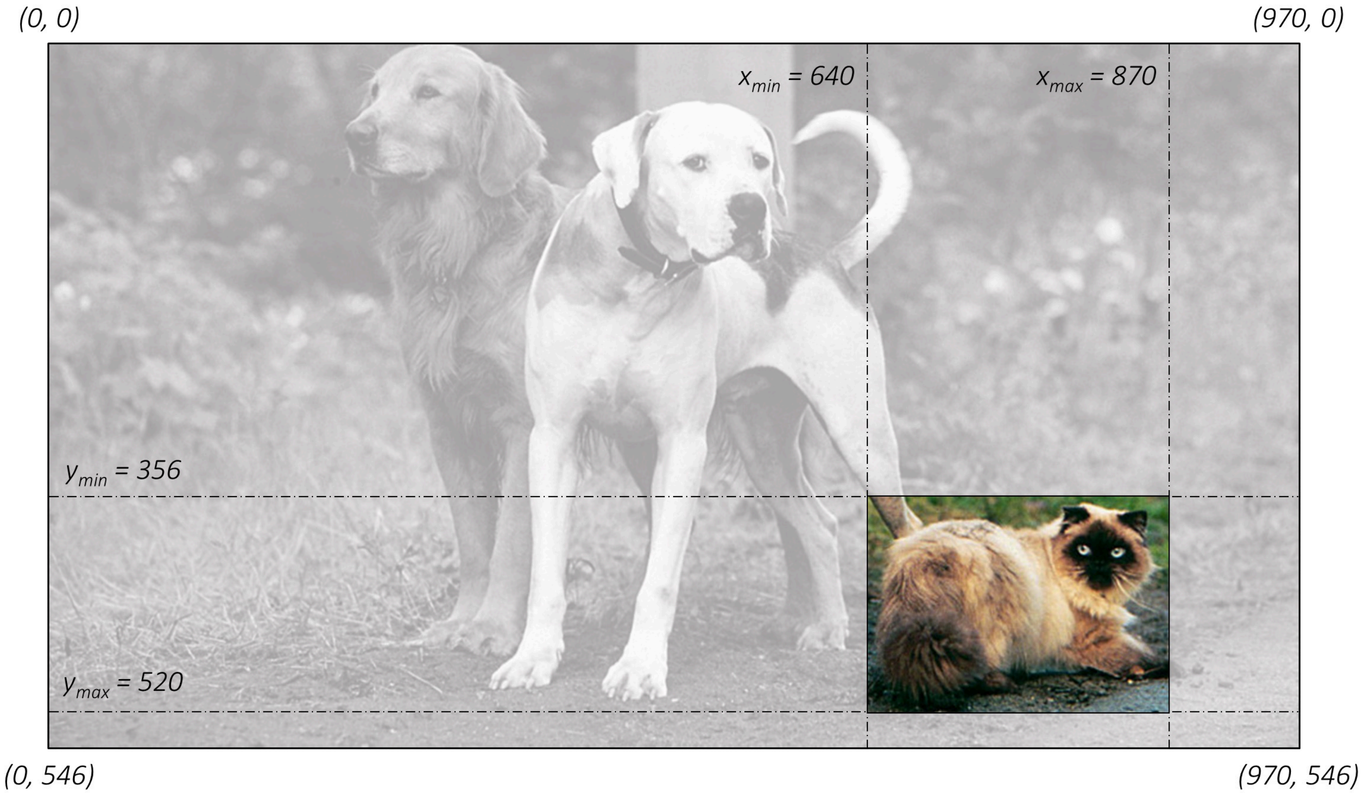


Image Classification, object detection

Image classification	Object detection

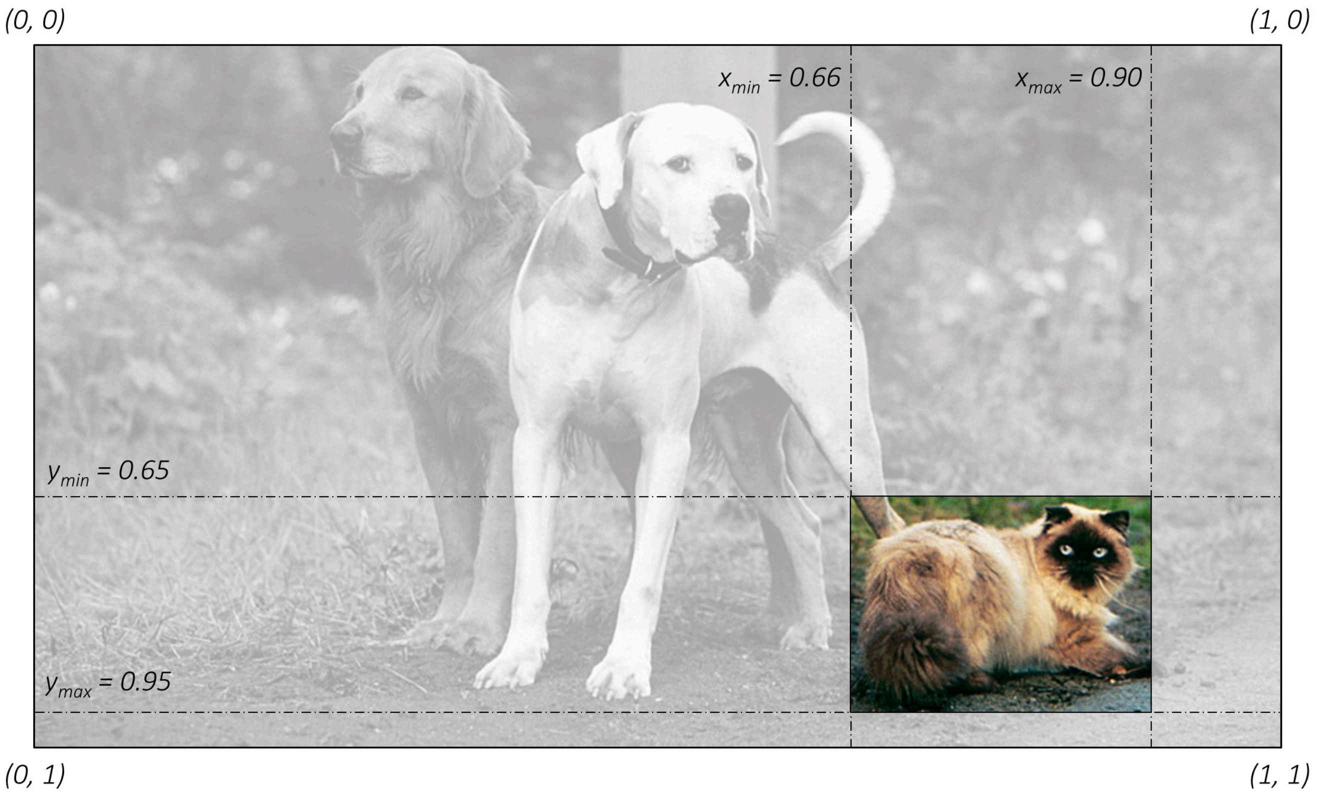
- What?
 	
- Input: un'immagine con uno o più oggetti
- Output: class label(s)
	- What? + Where?
	
	- input: un'immagine con uno o più oggeti
	- Output:
	  - uno o più bounding boxes
	  - Un'etichetta di classe per ogni bounding box

Bounding boxes



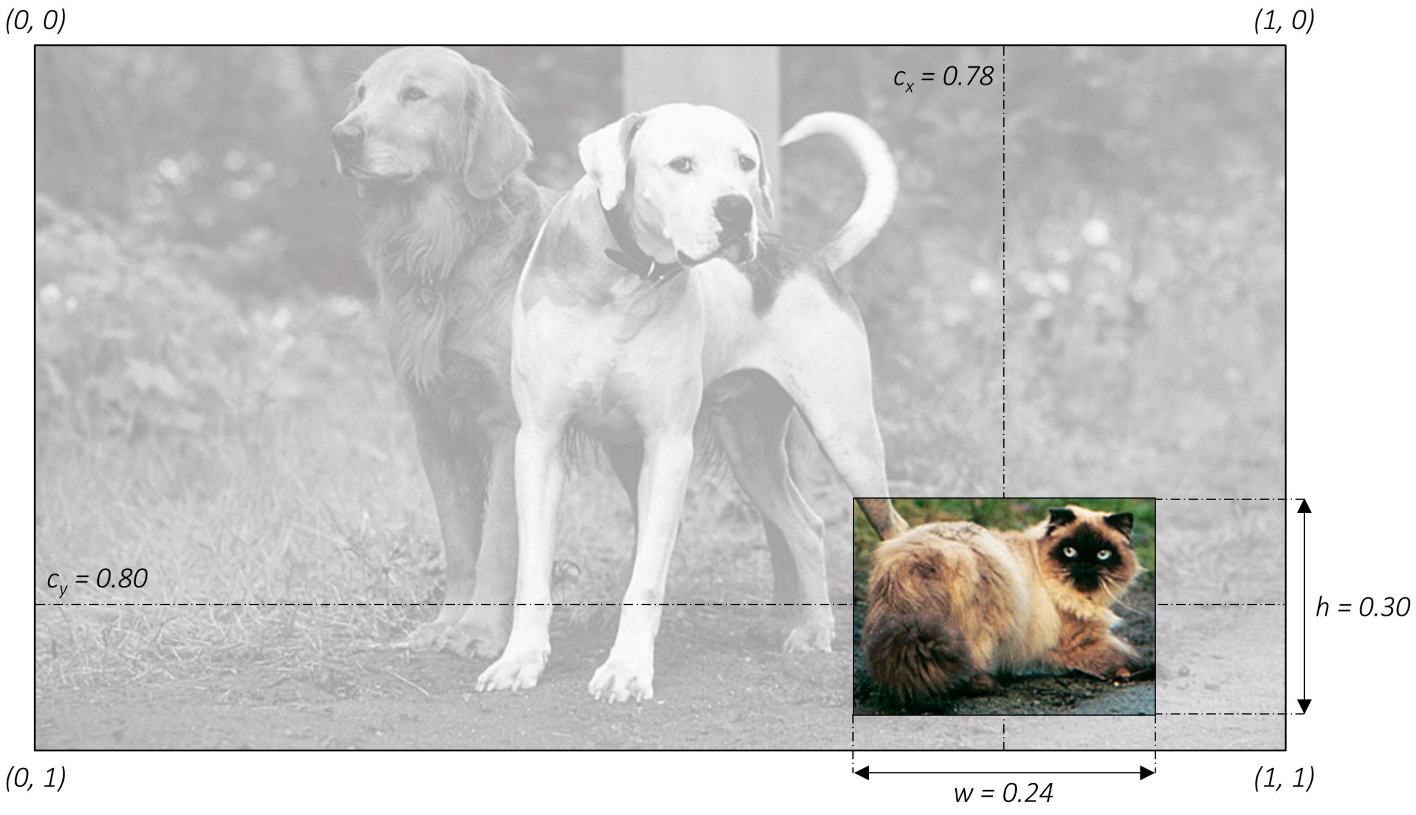
Boundary Coordinates (x_{min}, y_{min}, x_{max}, y_{max}) = (640, 356, 870, 520)

Bounding boxes



Boundary Coordinates $(x_{min}, y_{min}, x_{max}, y_{max}) = (0.66, 0.65, 0.90, 0.95)$

Bounding boxes



Center-Size Coordinates $(c_x, c_y, w, h) = (0.78, 0.8, 0.24, 0.30)$

Image Classification, object detection

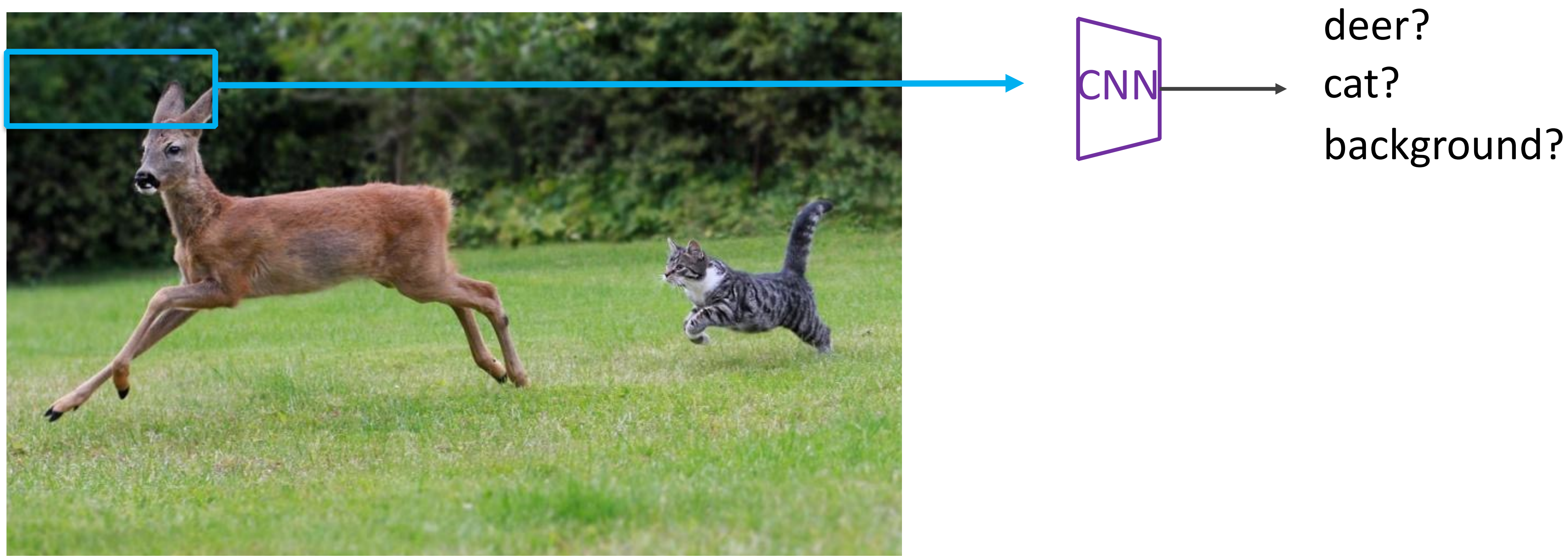
Image classification	Object detection

- What?
 	
- Input: un’immagine con uno o più oggetti
- Output: class label(s)
	- What? + Where?
	
	- input: un’immagine con uno o più oggeti
	- Output:
	    - uno o più bounding boxes
	        - (x, y, w, h)
	    - Un’etichetta di classe per ogni bounding box

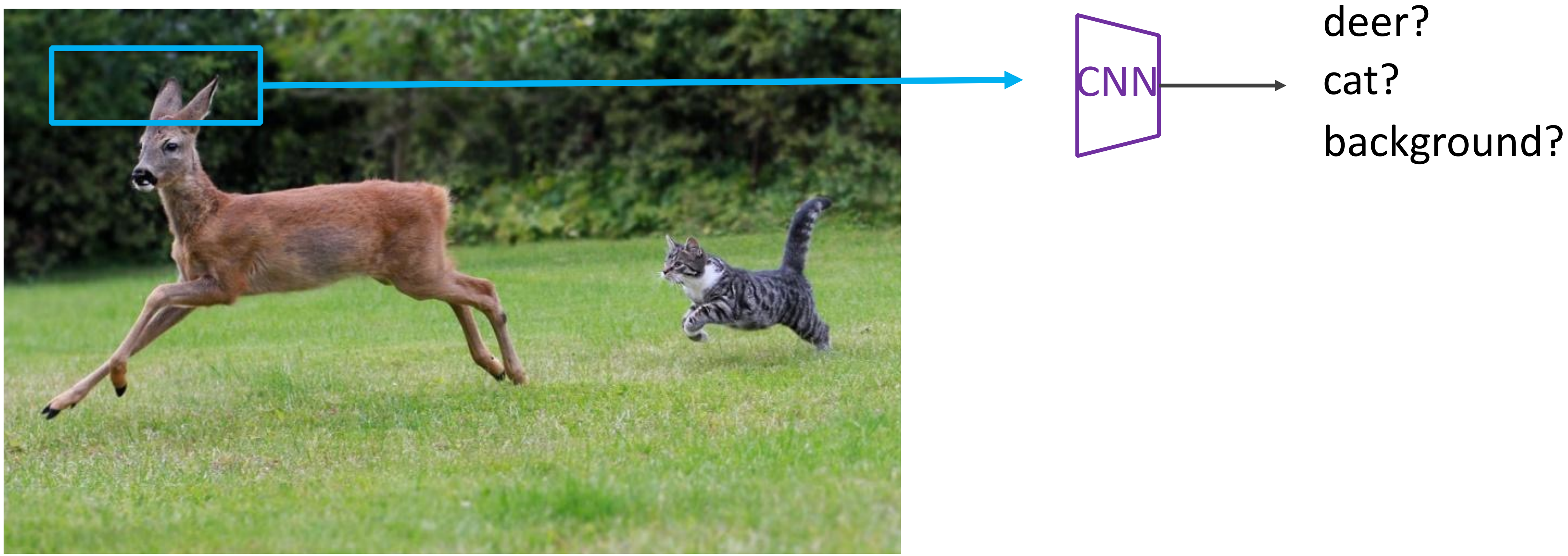
Approcci all’object detection

- Si esamina ogni posizione/scala
- Si utilizza qualche meccanismo propositivo per analizzare un insieme di regioni candidate

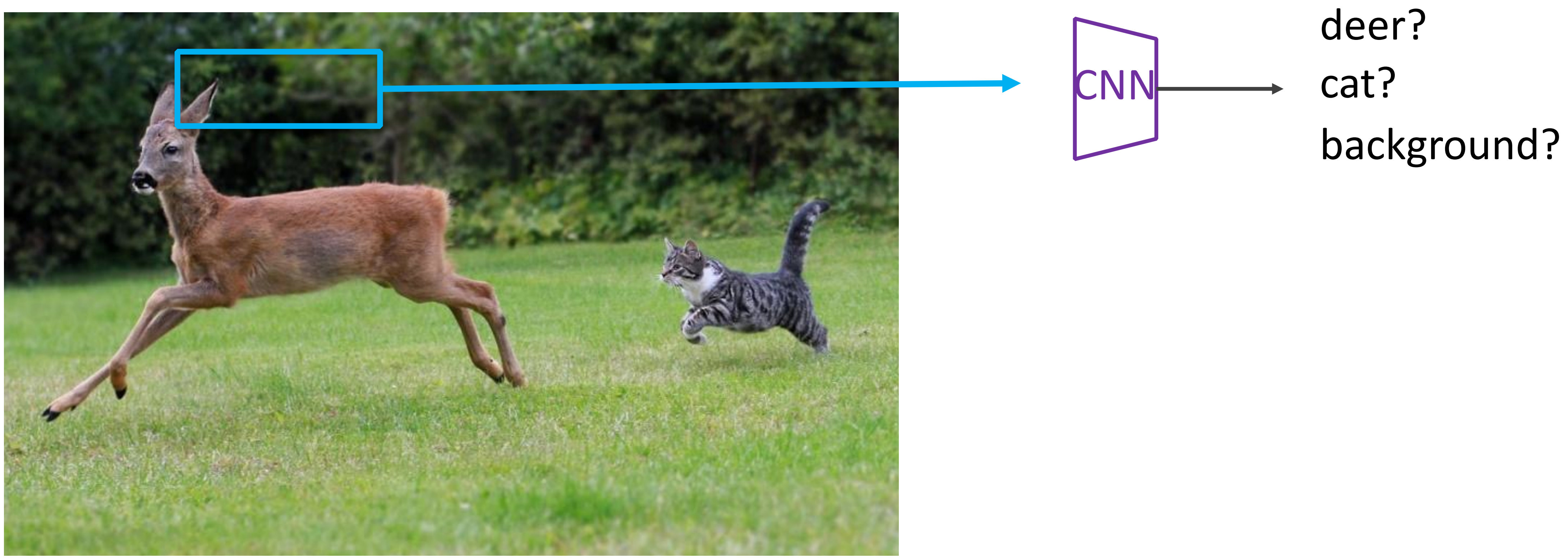
Sliding windows



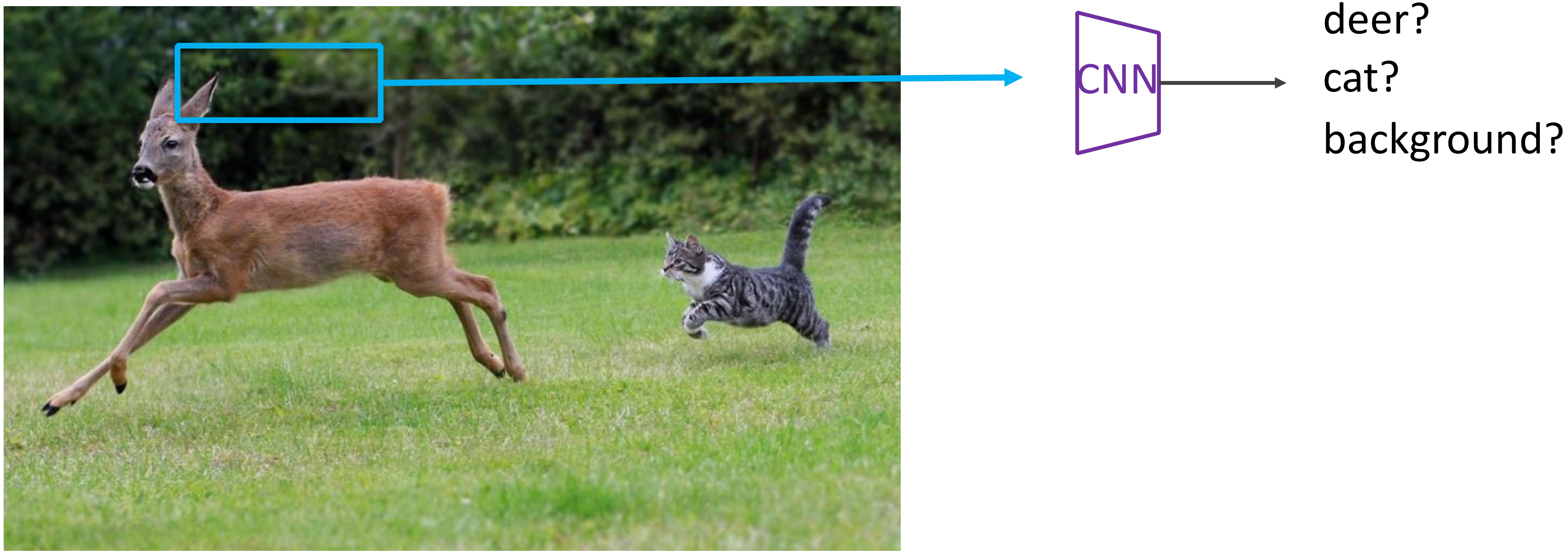
Sliding windows



Sliding windows

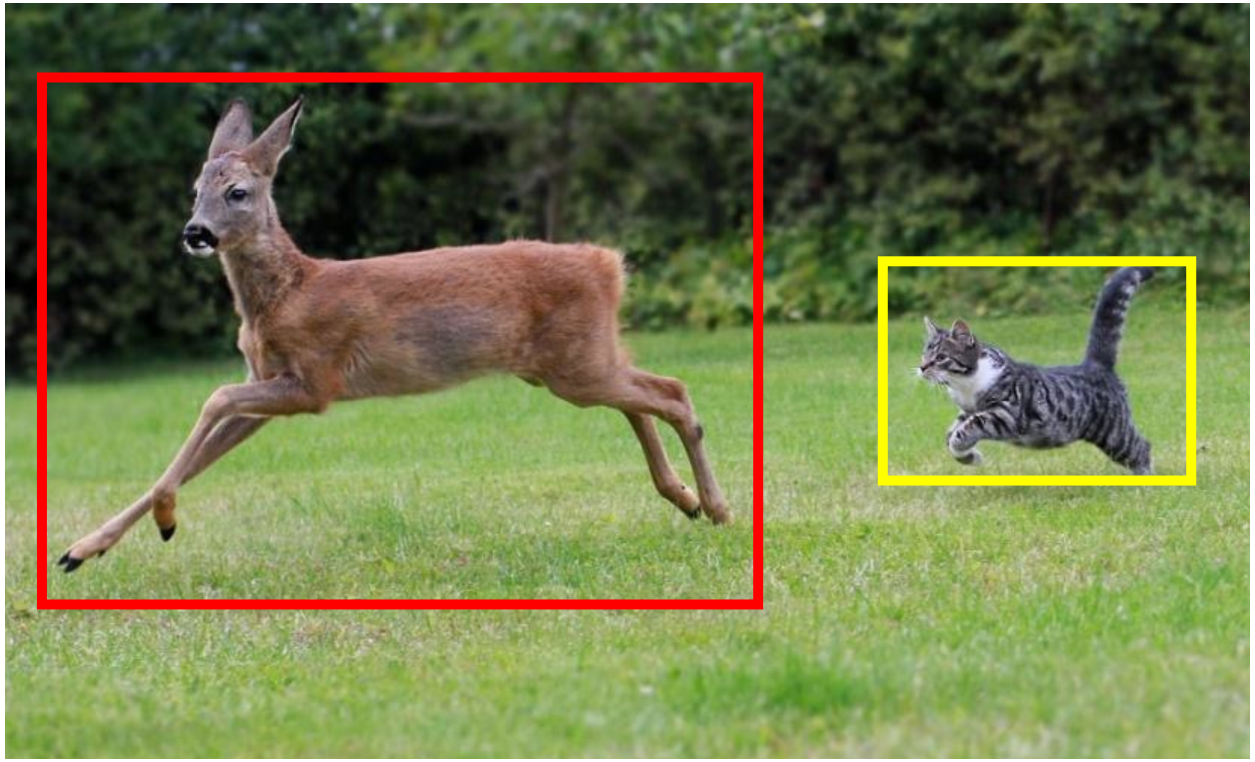


Sliding windows



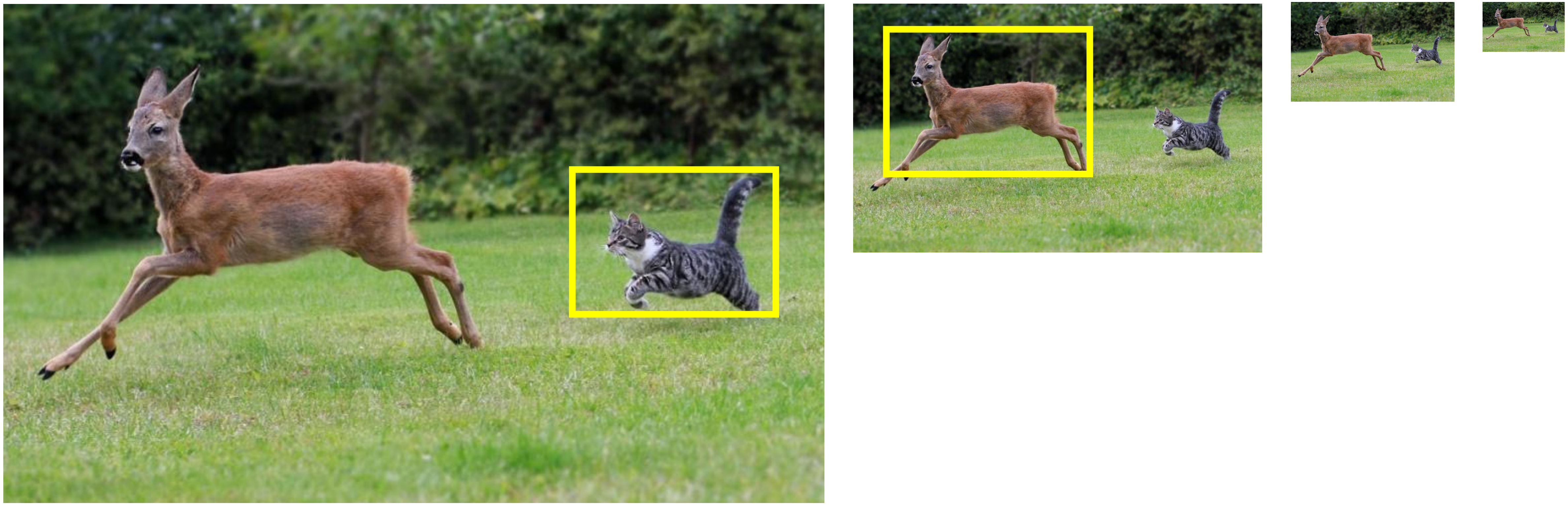
Sliding windows

- Esplosione combinatoria!
  - Dimensioni delle patch
  - Quantità di patch



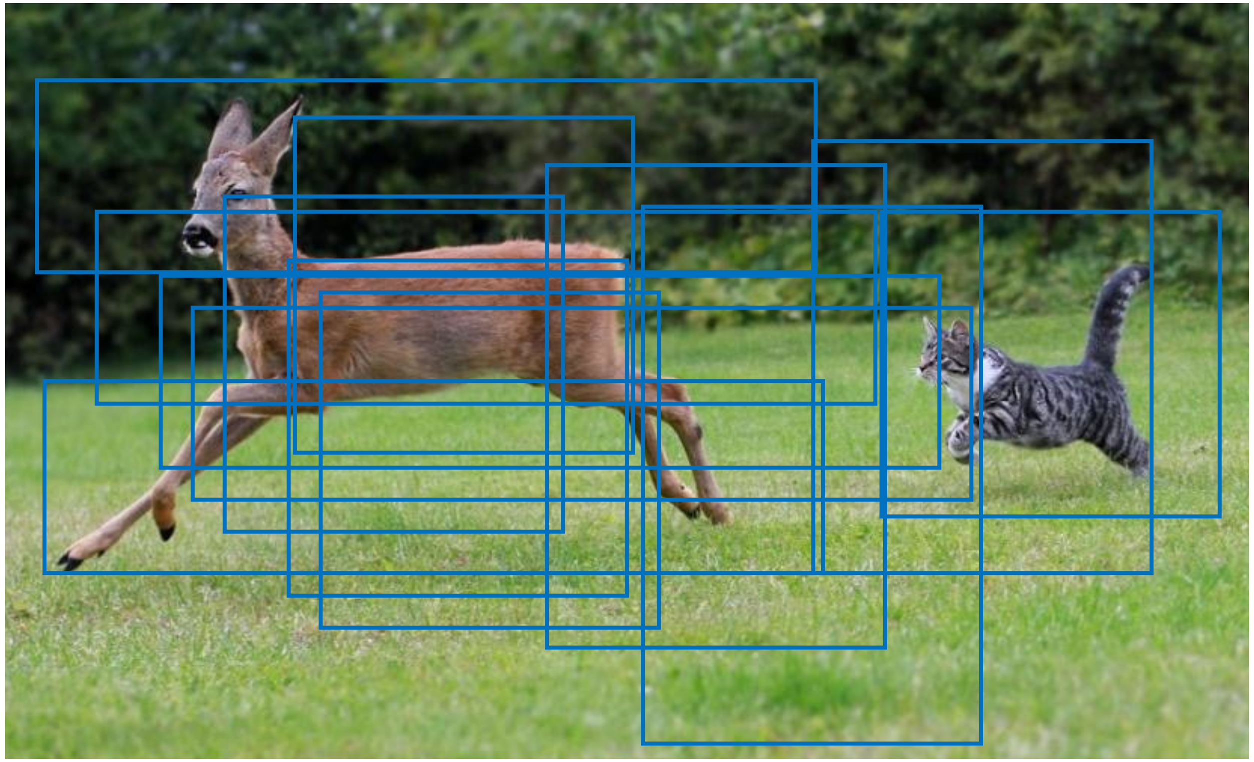
Approccio Naive

- Soluzione parziale: pyramids



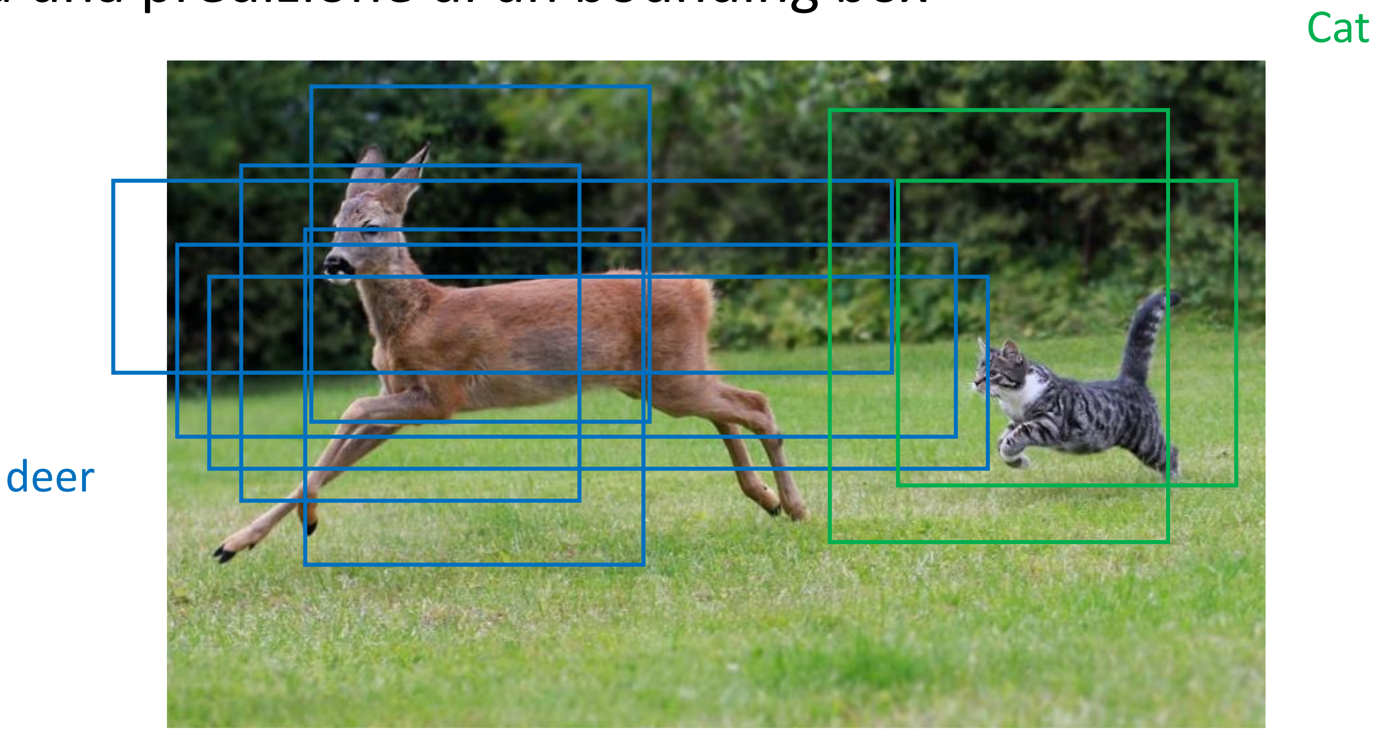
Region Proposals

- Si generano Regioni di interesse (ROI)



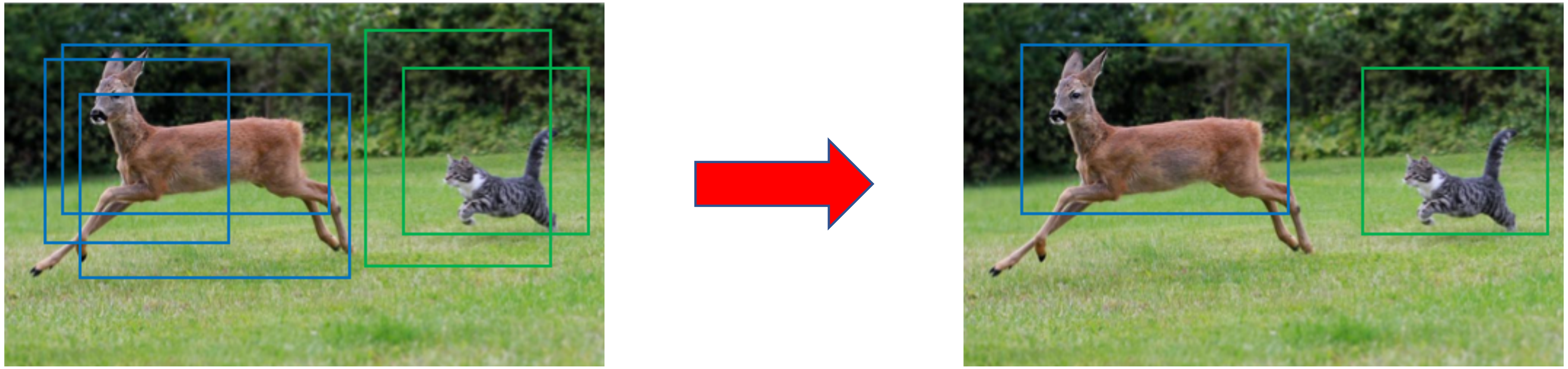
Region Proposals

- Si generano Regioni di interesse (ROI)
  - Algoritmo/modello di deep learning
- Feature extraction e predizioni sulle ROI
  - Su ogni ROI viene effettuata una predizione di un bounding box



Region Proposals

- Si generano Regioni di interesse (ROI)
  - Algoritmo/modello di deep learning
- Feature extraction e predizioni sulle ROI
  - Su ogni ROI viene effettuata una predizione di un bounding box
- Non-Maximum Suppression
  - I bounding box non ottimali vengono rimossi

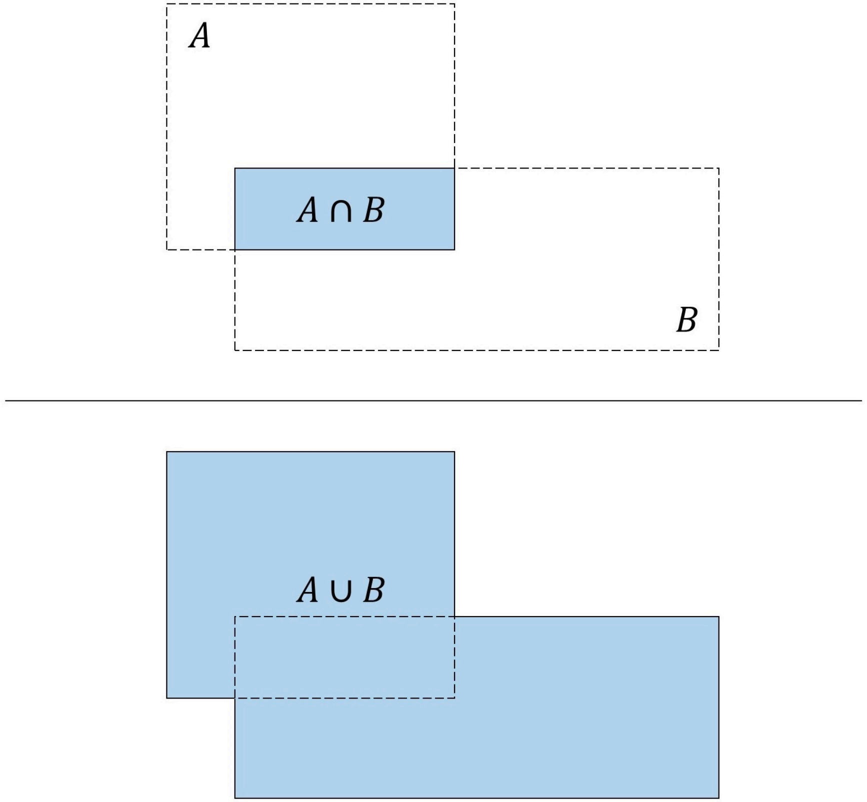


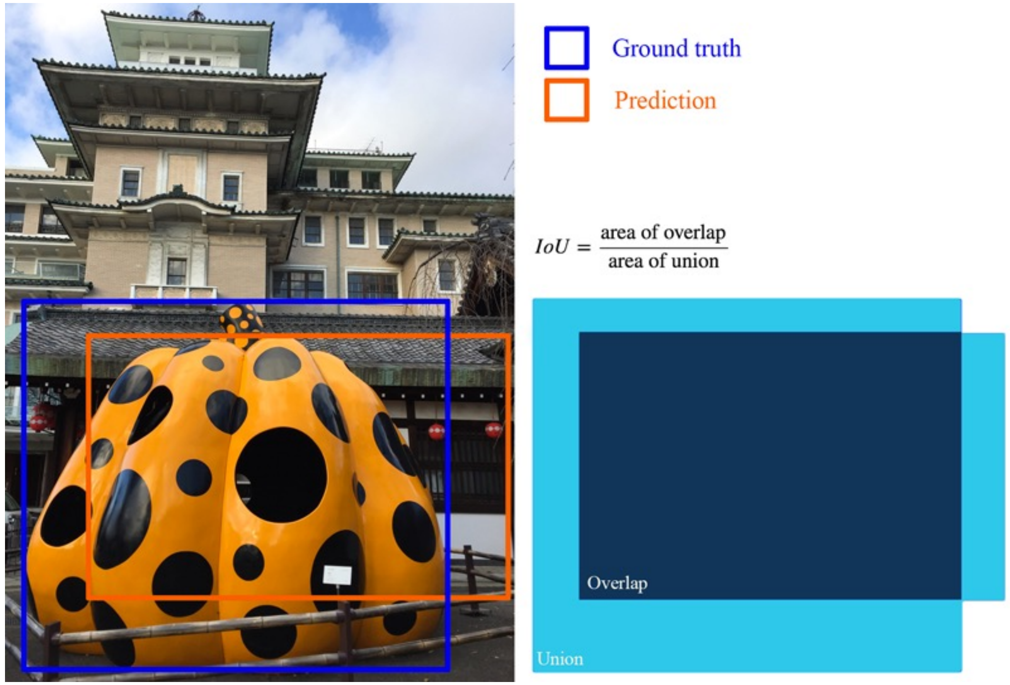
Qualità di un object detector

- FPS
  - frames per second (FPS)
  - Quante immagini al secondo si è in grado di analizzare
- Precision/Recall, mean Average Precision (mAP)
  - Intersection over Union

Intersection over Union

$$IoU = \frac{A \cap B}{A \cup B} =$$





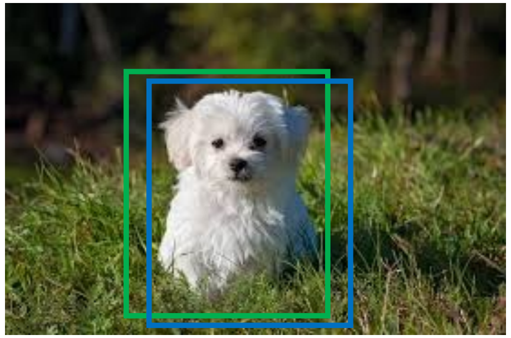
Precision, Recall

- True Positives (TP), False Positives (FP), True Negatives (TN), False Negatives (FN)

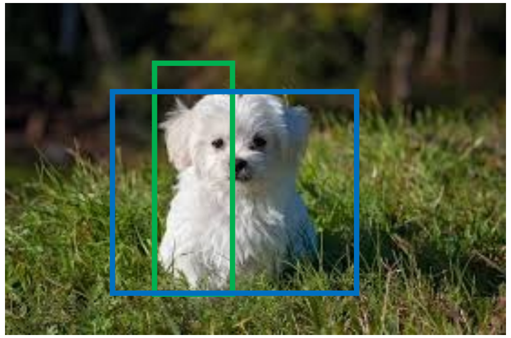
$$Prec = \frac{TP}{TP + FP} \qquad\qquad Rec = \frac{TP}{TP + FN}$$

- Riferito ad un match
  - Dato un bounding box predetto e uno «ground truth»
    - True Positive se $IoU > \theta$, con θ valore di soglia, altrimenti False Positive

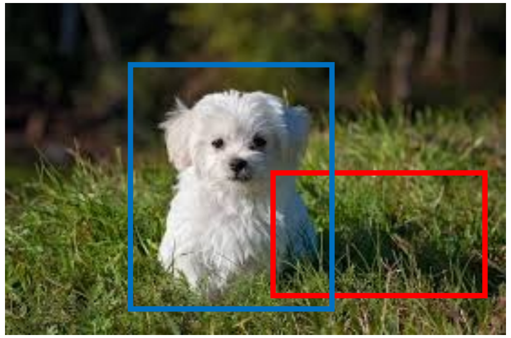
TP



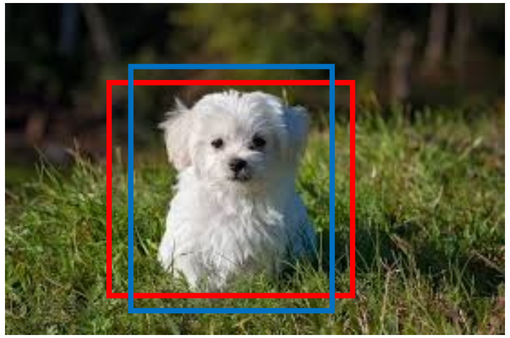
FP



TN



FN



Precision/Recall

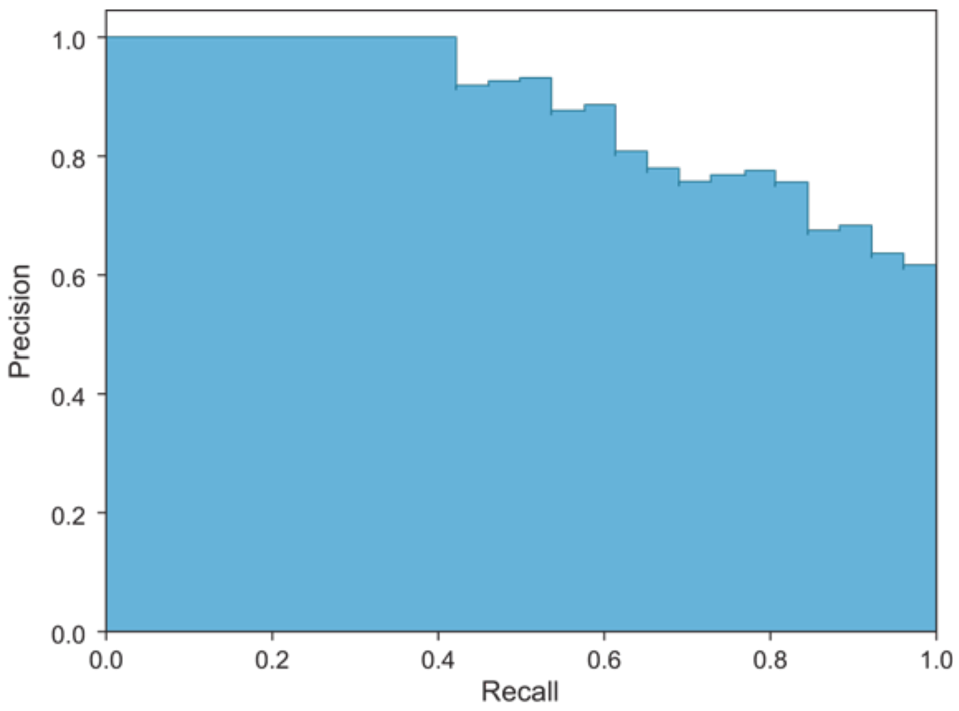
- Valori di Precision/recall al variare di θ, riferito agli oggetti di classe c

$$AP_c = \int_0^1 Prec_c(\,\theta)d\theta$$

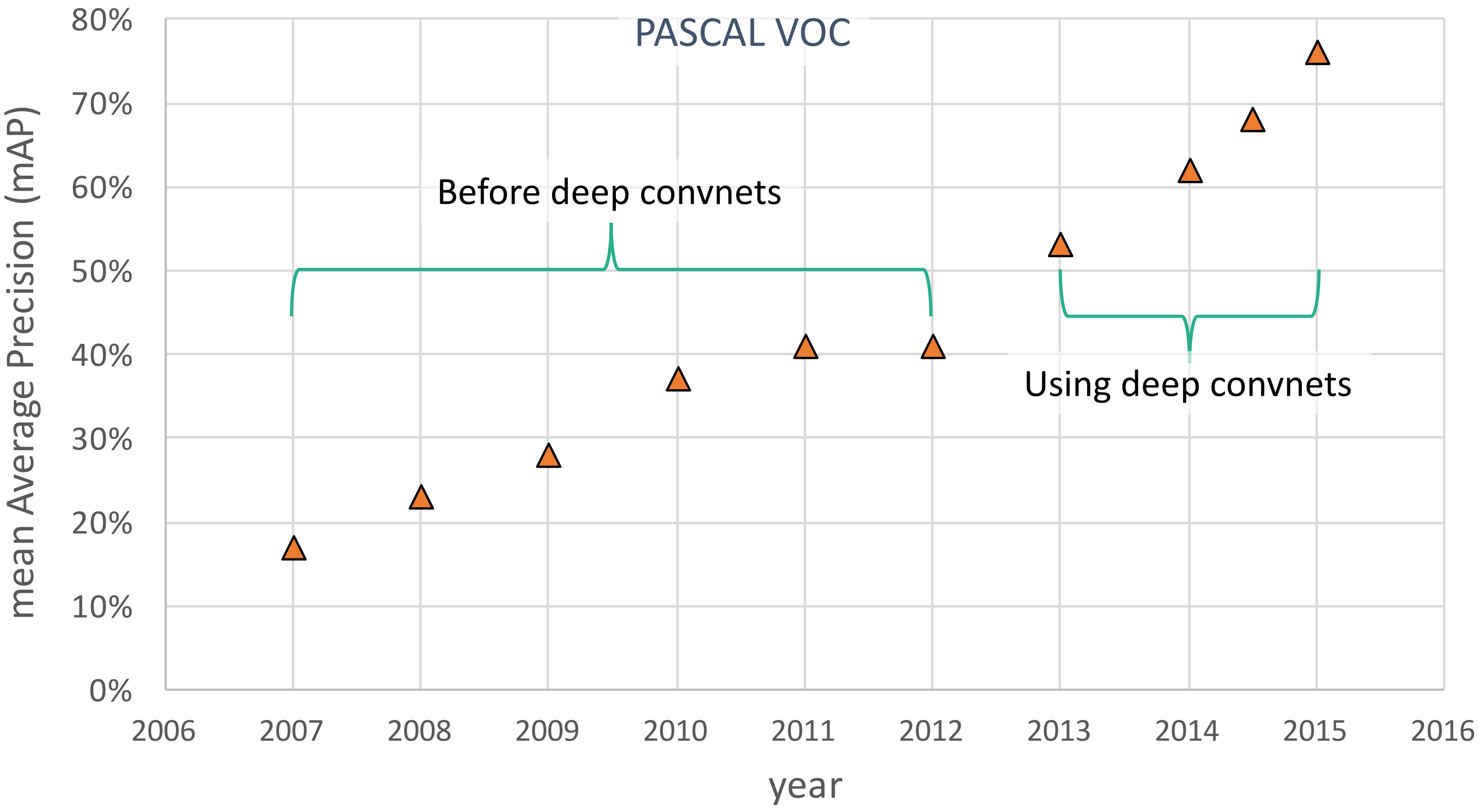
  - In genere si può calcolare a gradoni, raccogliendo tutti i possibili valori di soglia

$$mAP = avg_c(AP_c)$$

$$mAP@\theta = avg_c(Prec_c(\theta))$$



Evoluzione

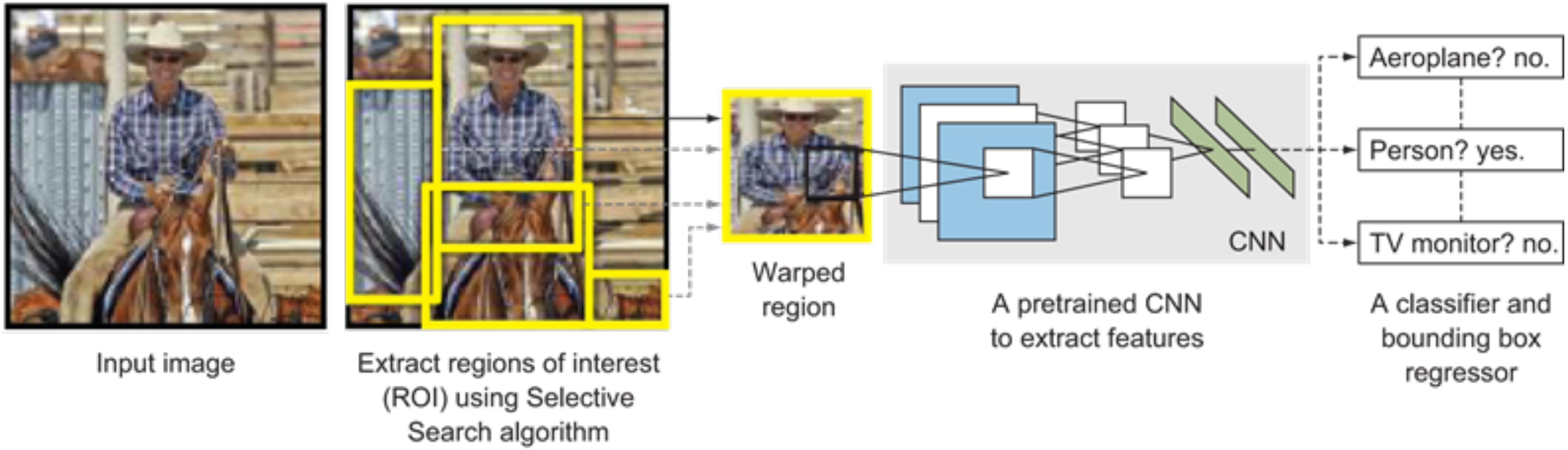

PASCAL VOC
mean Average Precision (mAP)
80%
70%
60%
50%
40%
30%
20%
10%
0%
Before deep convnets
Using deep convnets
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
year

Approcci

- Multi-shot detectors
  - R-CNN
  - Fast R-CNN
  - Faster R-CNN
- Single-Shot detectors
  - SSD
  - YOLO

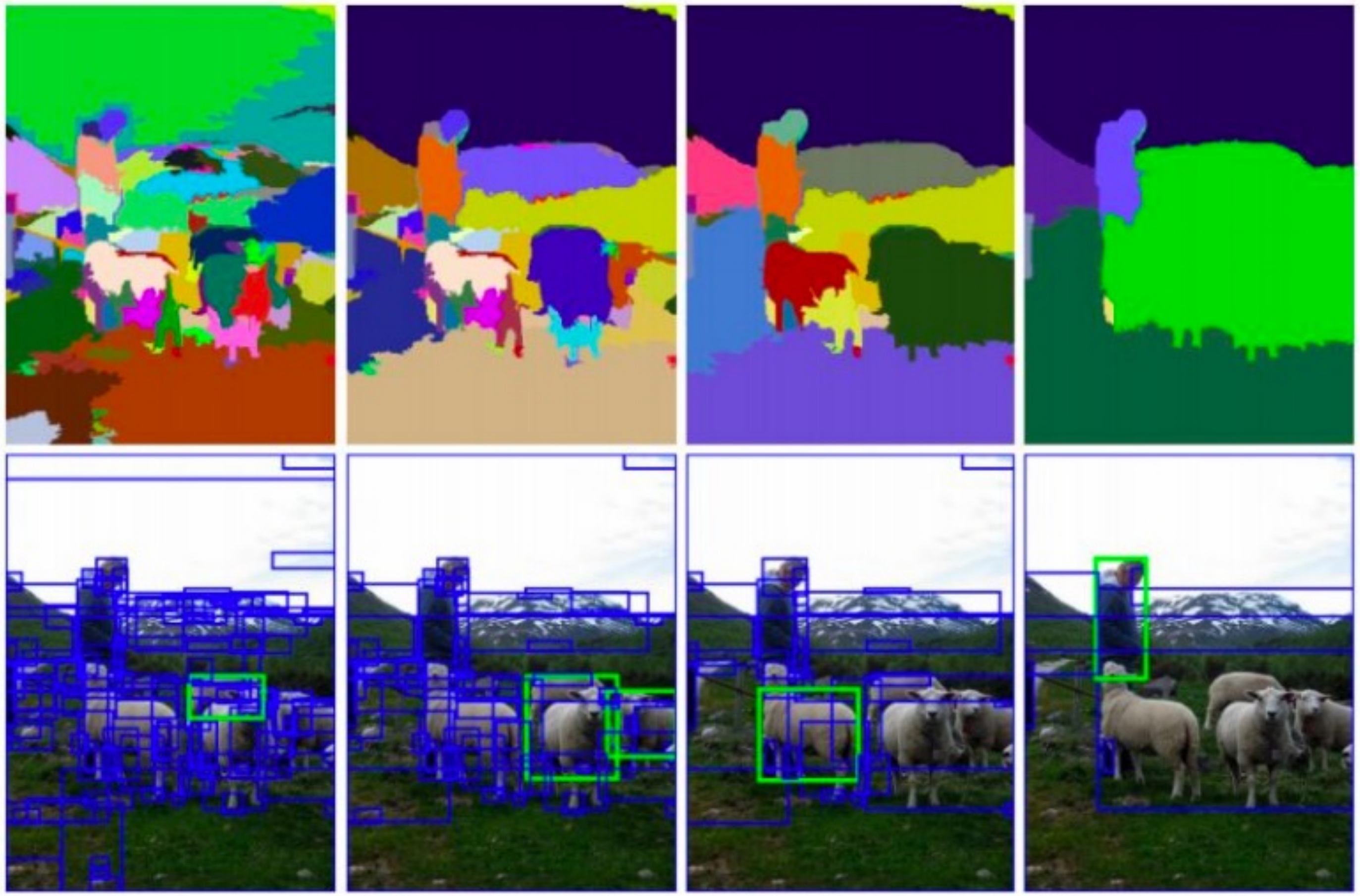
Region-Based Convolutional Neural Networks (R-CNN)

- Ross Girshick et al., 2014

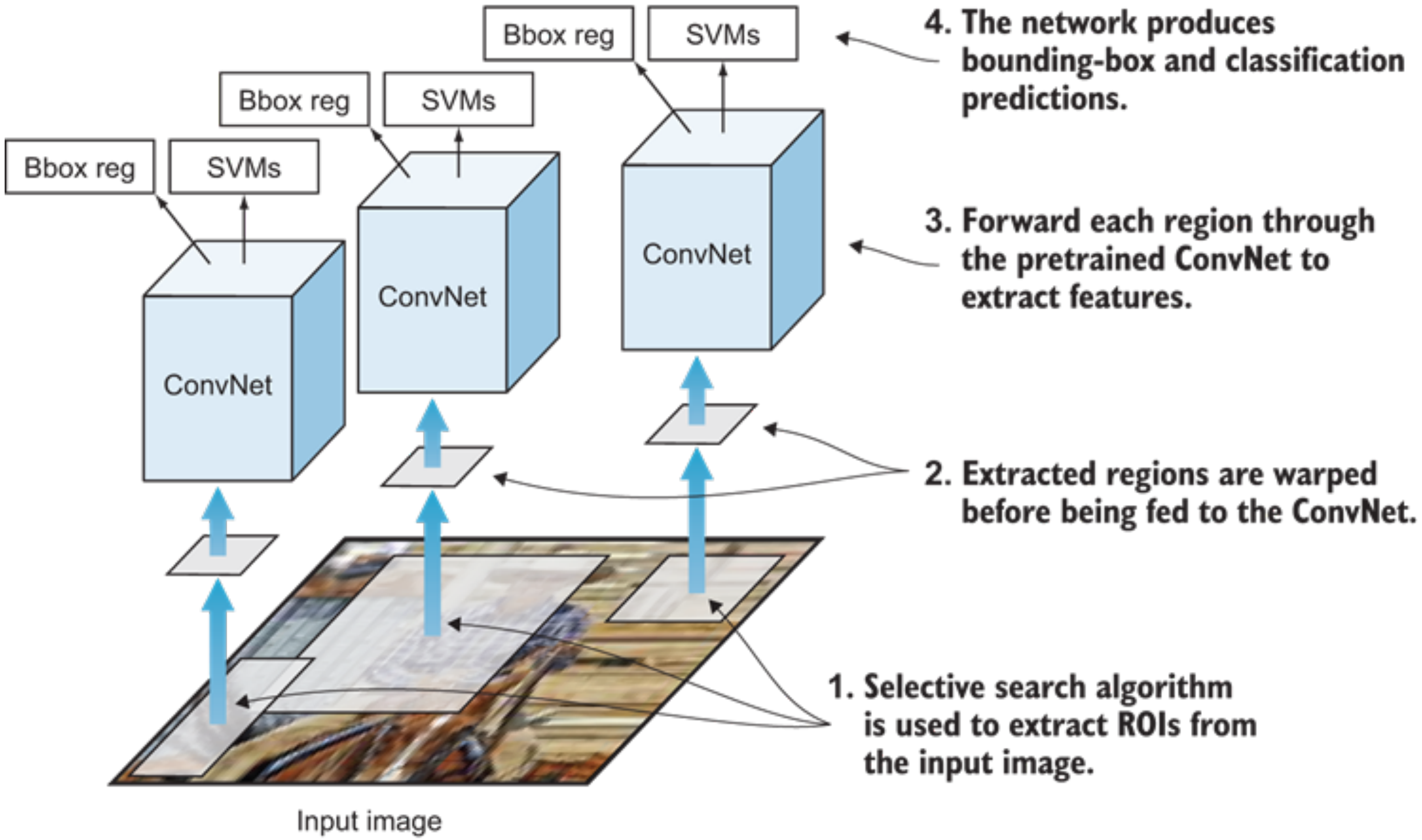


Selective Search

- Si segmenta l'immagine usando un algoritmo graph-based
  - Bounding box per ogni segmento
- Progressivamente si uniscono i bounding box sulla base della loro vicinanza e somiglianza
  - Colore, texture, …



Feature extraction e predizione



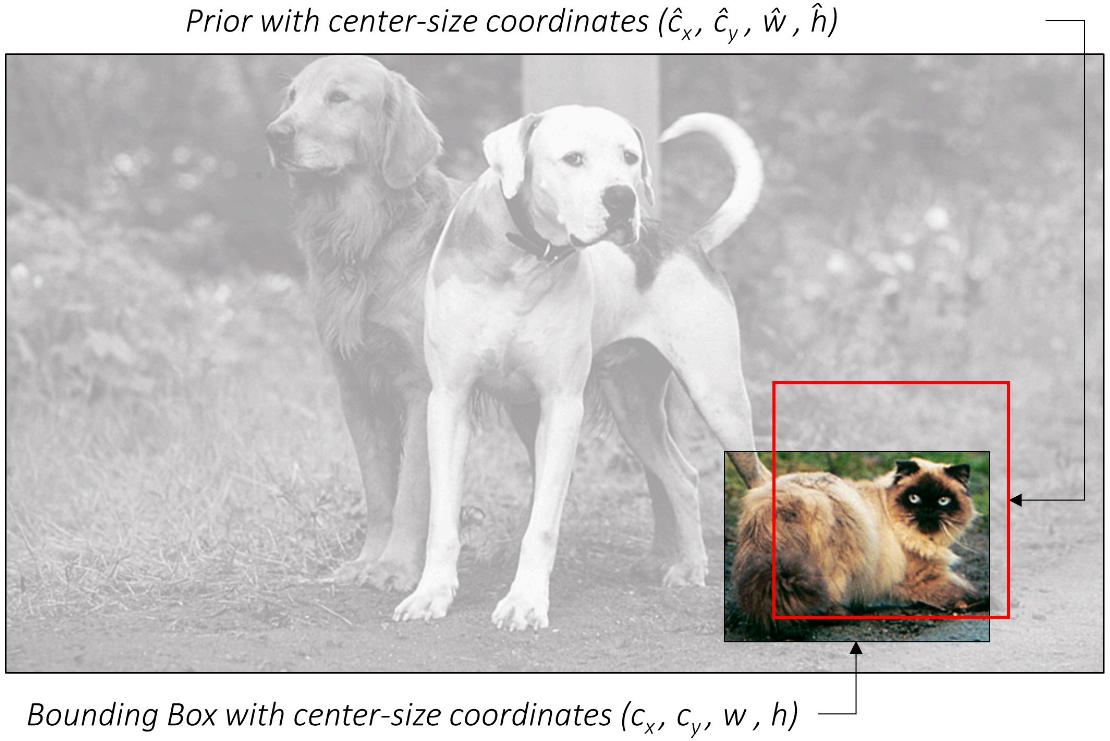
Bounding Box Regression

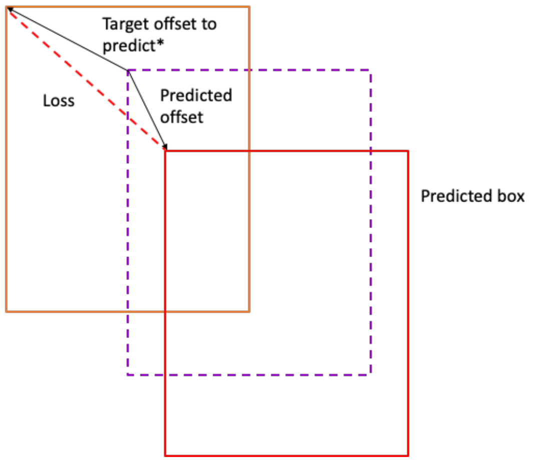
- Le coordinate (c_x, c_y, w, h) possono essere espresse in termini di offset $(g_{c_x}, g_{c_y}, g_w, g_h)$ rispetto alle coordinate $(\hat{c}_x, \hat{c}_y \hat{w}, \hat{h})$ della prior proposal region

$$g_{c_x} = \frac{c_x - \hat{c}_x}{\hat{w}} \qquad g_{c_y} = \frac{c_y - \hat{c}_y}{\hat{h}}$$

$$g_w = log\left(\frac{w}{\hat{w}}\right) \qquad g_h = log\left(\frac{h}{\hat{h}}\right)$$

- Regressione su $(g_{c_x}, g_{c_y}, g_w, g_h)$



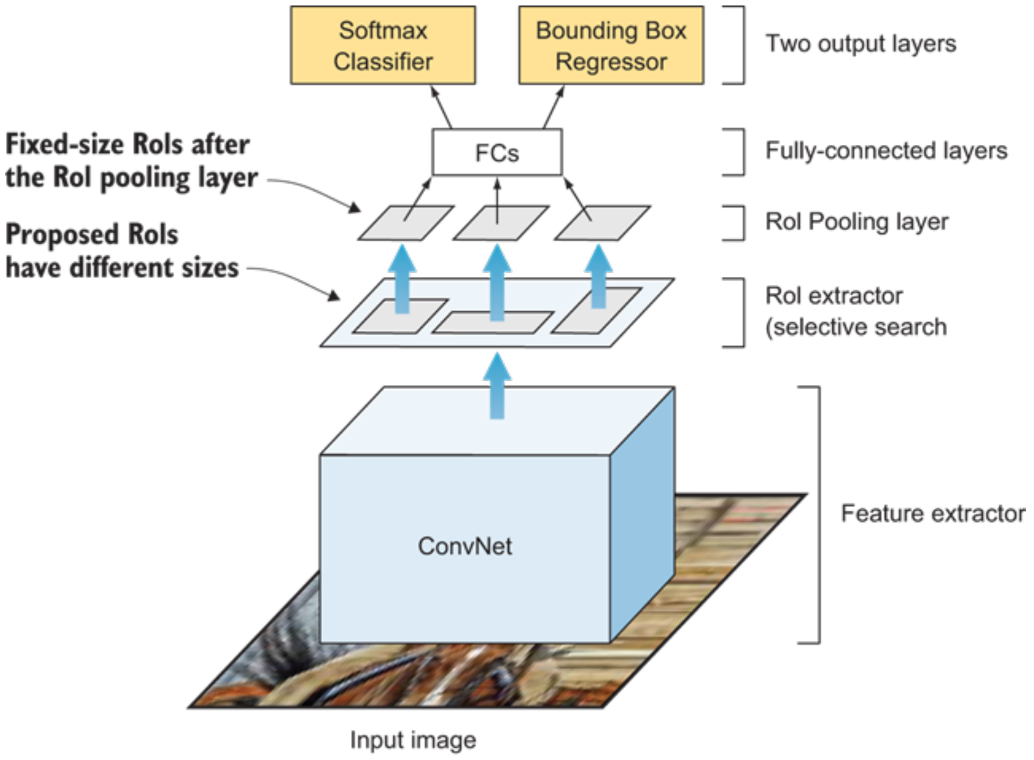


R-CNN

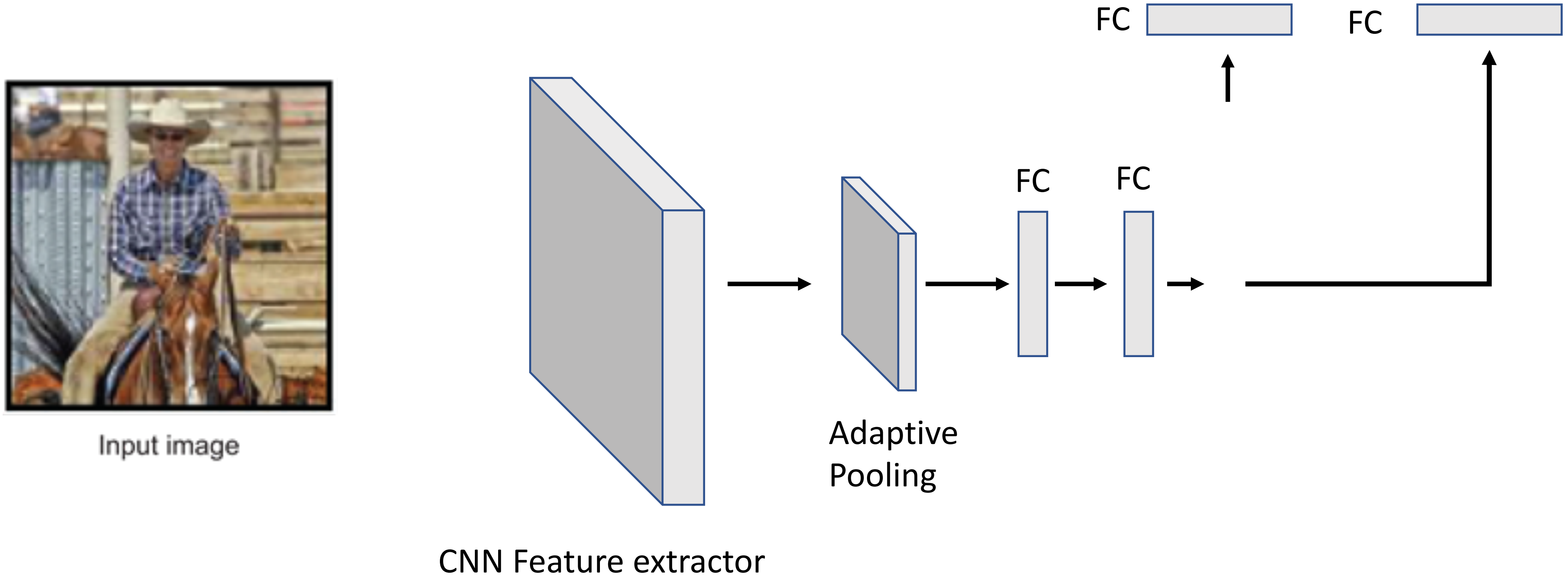
- Algoritmo lento
  - La fase SS genera 2000 blocchi candidati che devono essere passati al FE e al classificatore
  - ~47s/image = 0.021FPS
- Training multi-stage
  - Ogni modulo appreso separatamente
  - Estremamente lento (~84 ore)
  - Space complexity
- mAP 66%

Fast R-CNN

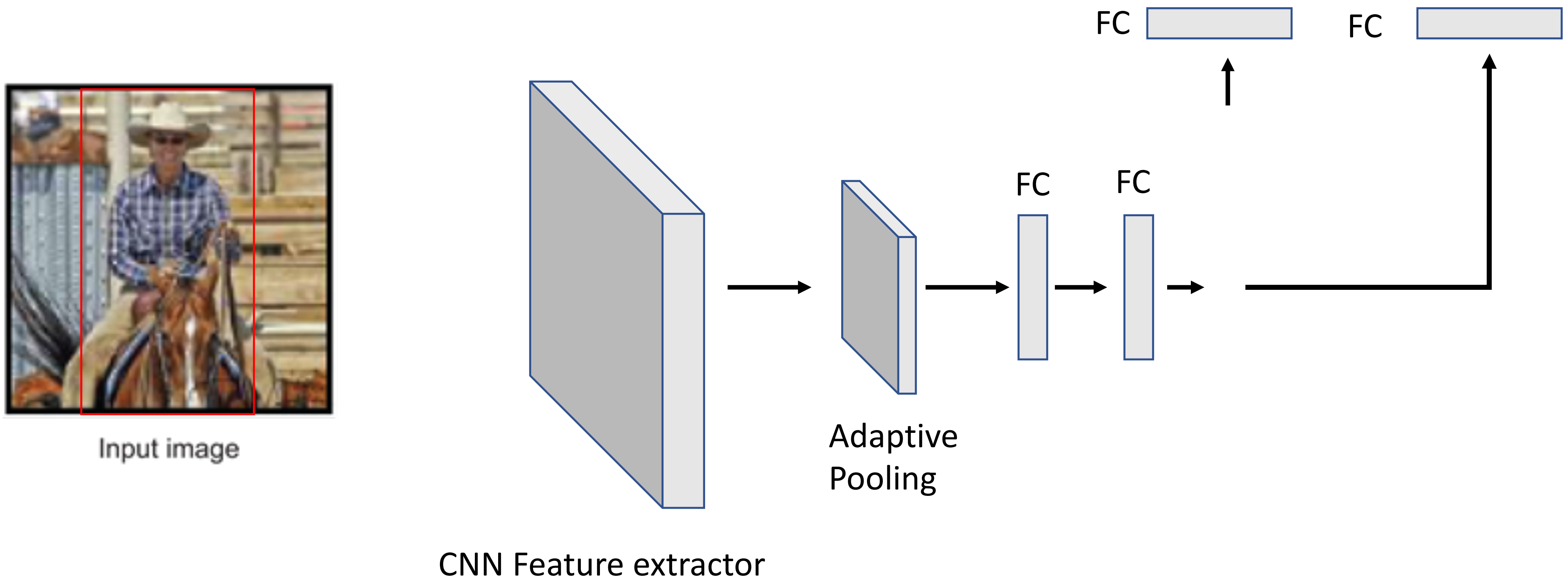
- Girshick, 2015
- Idea: utilizziamo un unico feature extractor e integriamo un modulo di classificazione



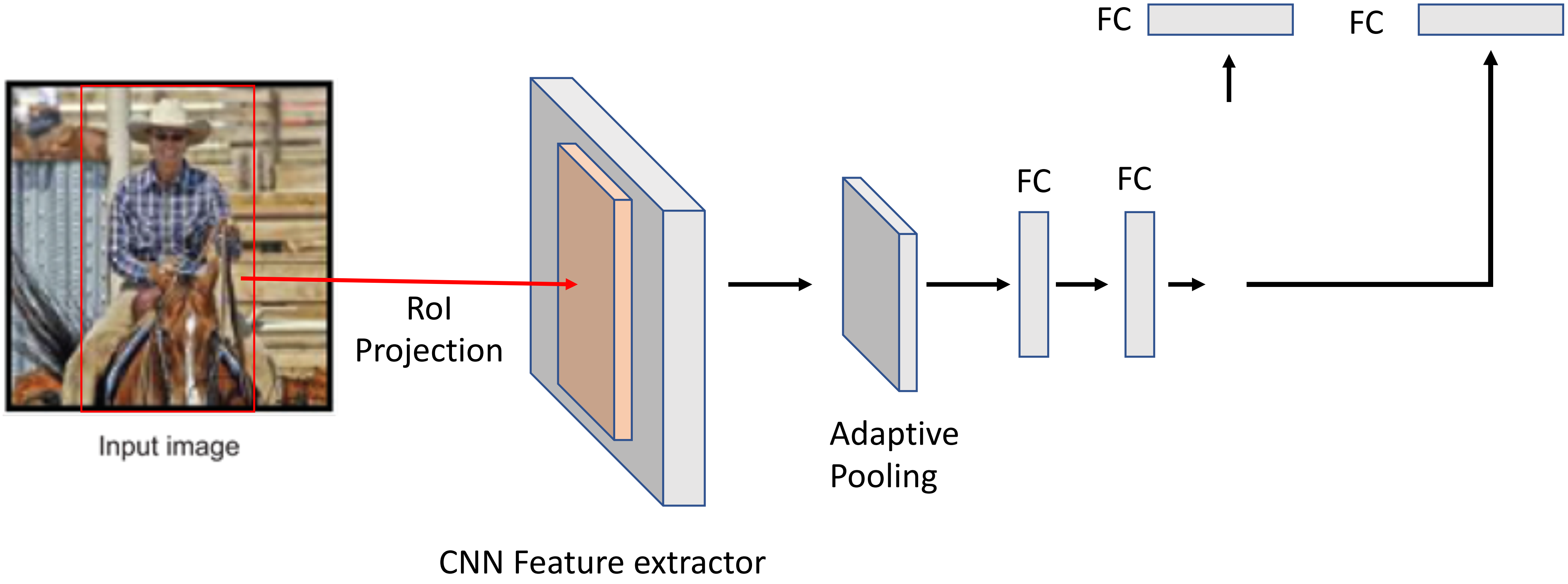
Fast R-CNN


Input image
CNN Feature extractor
Adaptive
Pooling
FC
FC
FC
FC

Fast R-CNN

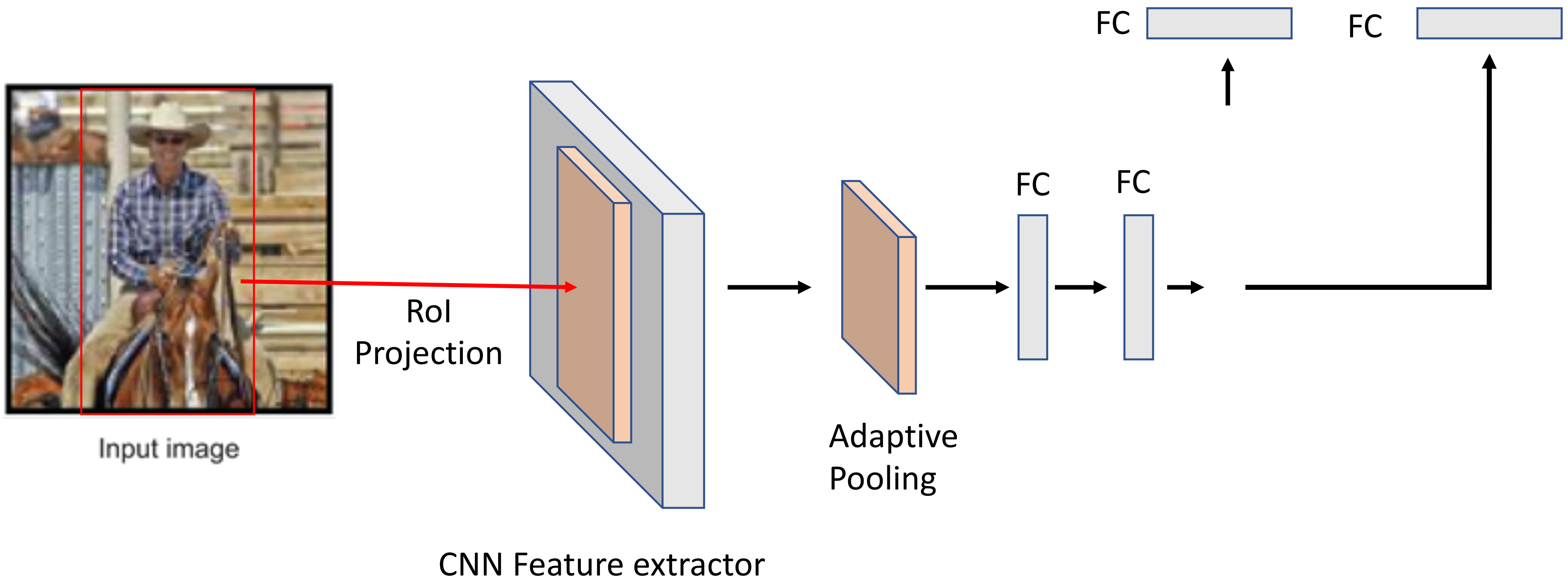

FC
FC
FC
FC
Input image
Adaptive
Pooling
CNN Feature extractor

Fast R-CNN

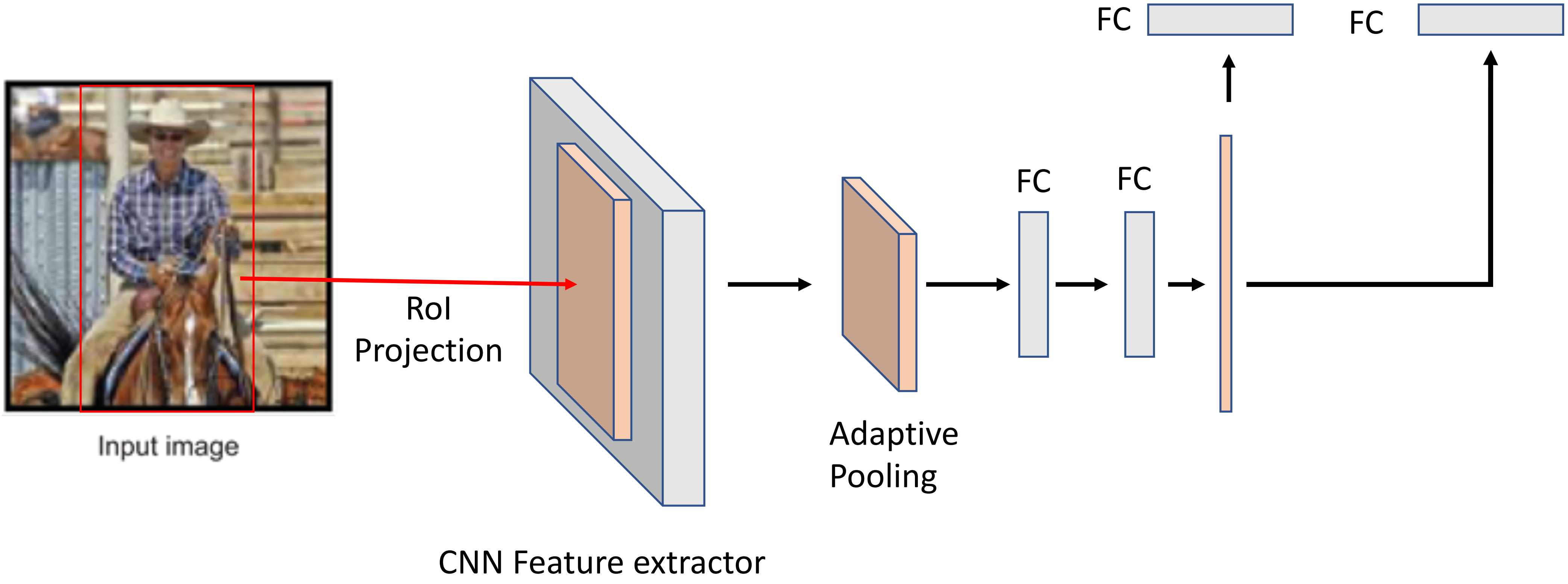


FC
FC
RoI
Projection
Input image
Adaptive
Pooling
FC
FC
CNN Feature extractor

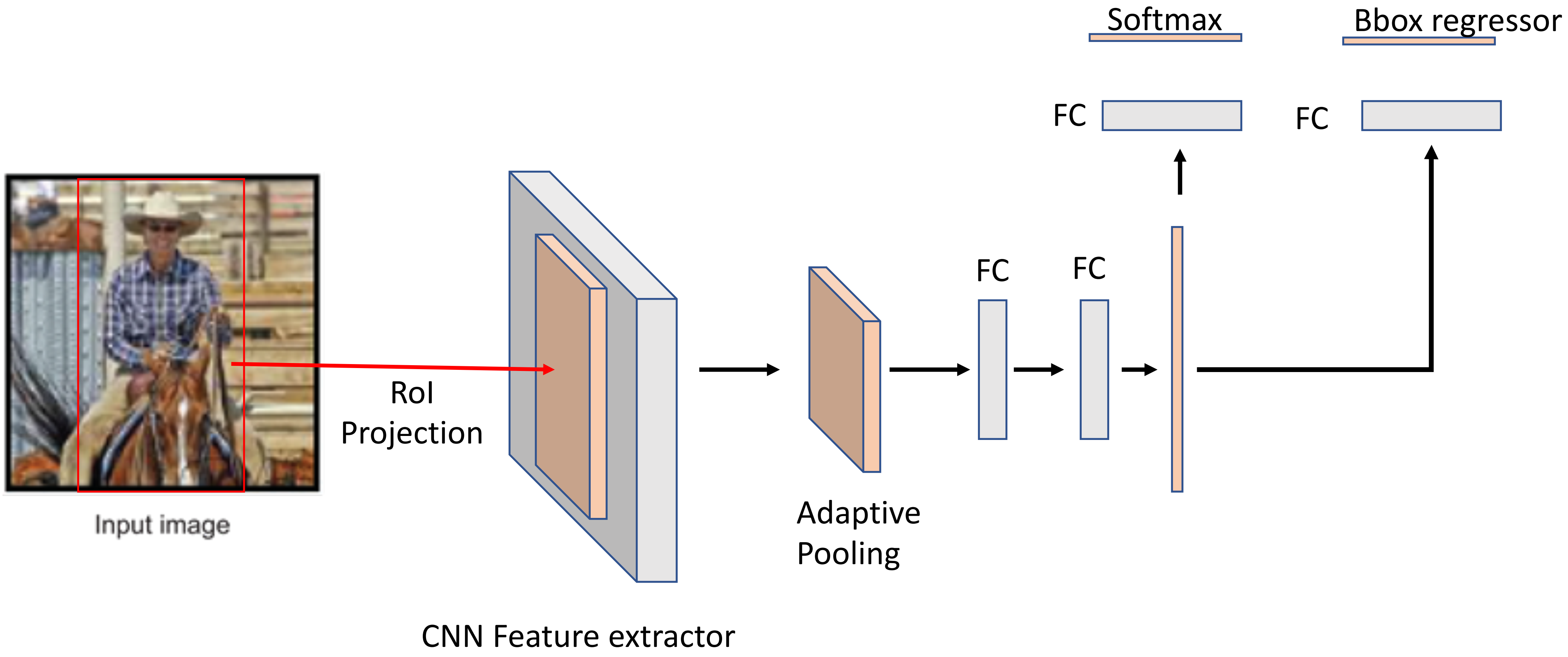
Fast R-CNN


FC
FC
FC
FC
RoI
Projection
Input image
Adaptive
Pooling
CNN Feature extractor

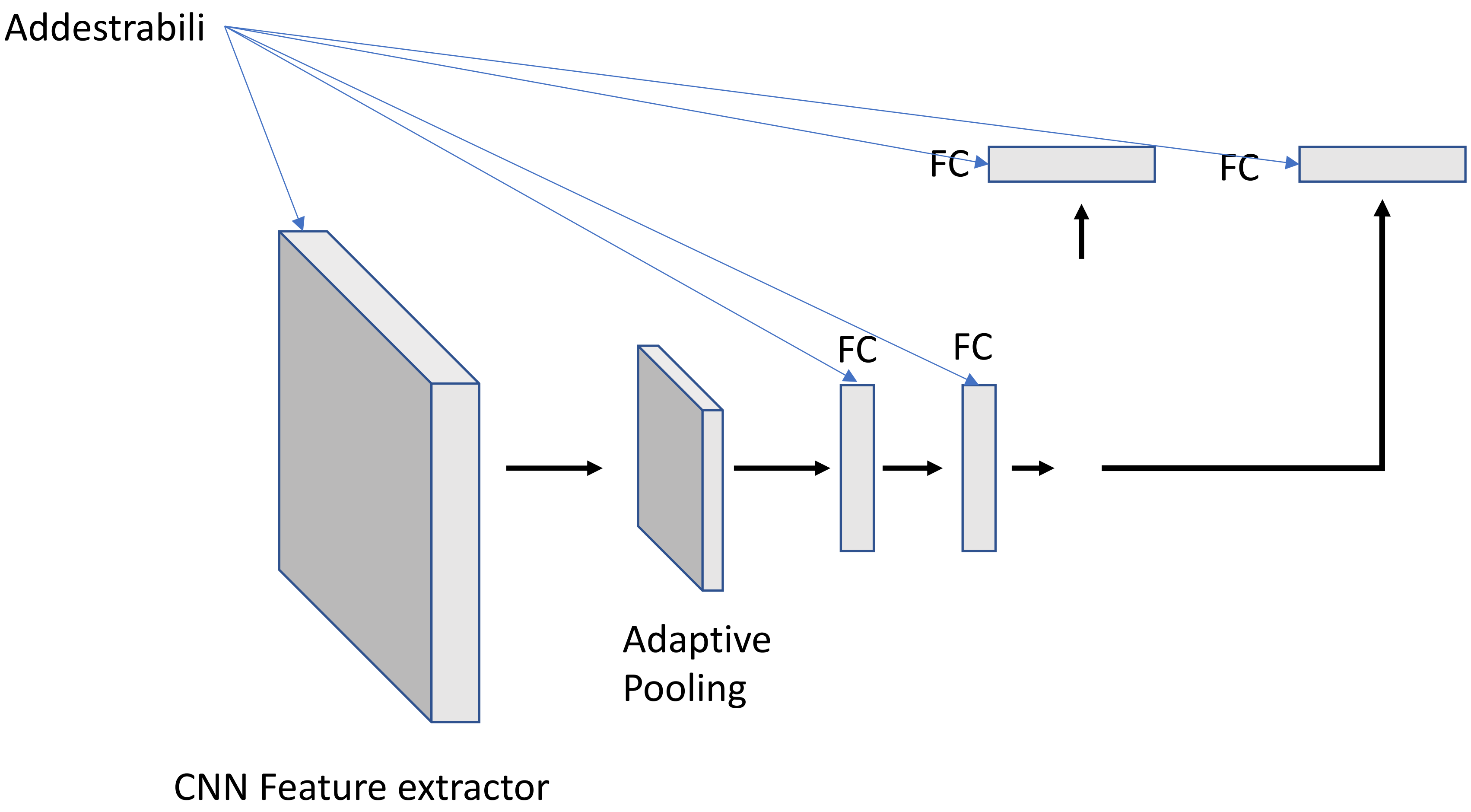
Fast R-CNN


FC
FC
FC
FC
RoI
Projection
Input image
Adaptive
Pooling
CNN Feature extractor

Fast R-CNN

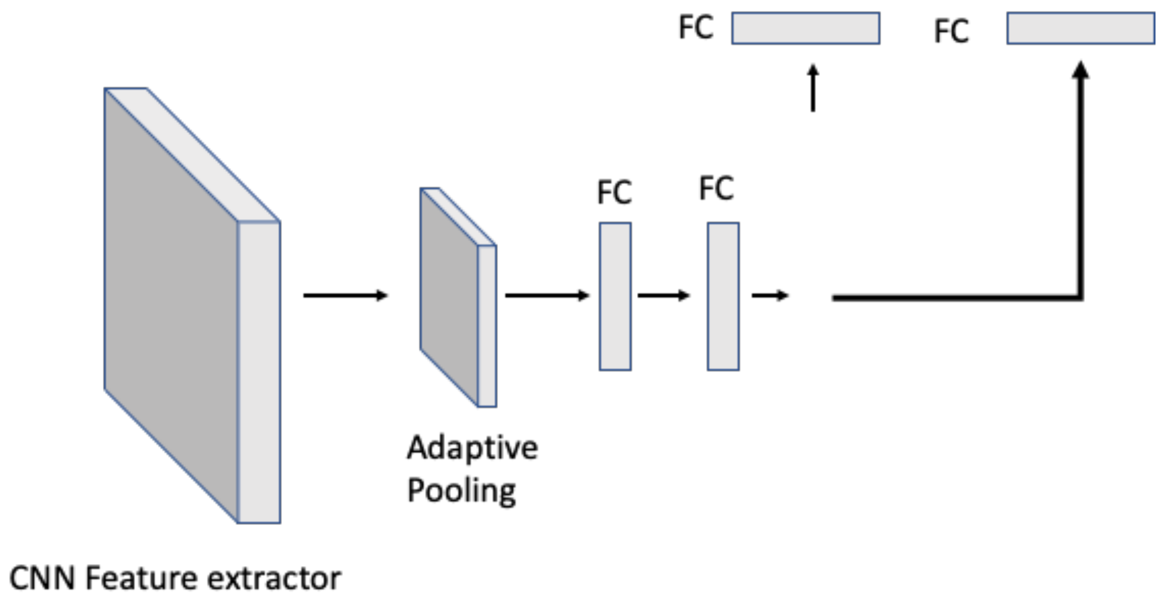

Softmax
Bbox regressor
FC
FC
FC
FC
RoI
Projection
Input image
Adaptive
Pooling
CNN Feature extractor

Fast R-CNN


Addestrabili
FC
FC
FC
FC
Adaptive
Pooling
CNN Feature extractor

Fast R-CNN

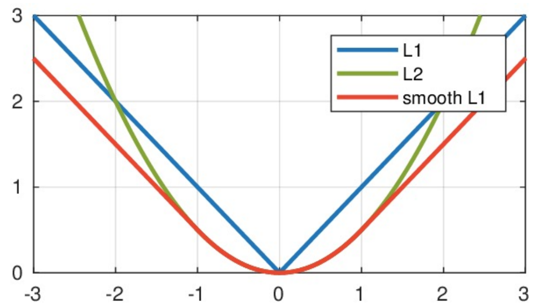
- Un oggetto $o_i = (y_i, c_i)$
  - $c_i = (c_{i,x}, c_{i,y}, c_{i,w}, c_{i,h})$
- Un box $b_i = (\hat{p}_i, \hat{c}_i)$



$$loss(o_i) = L_{CE}(\hat{p}_i, y_i) + [y_i > 0] L_{smooth}(c_i, \hat{c}_i)$$

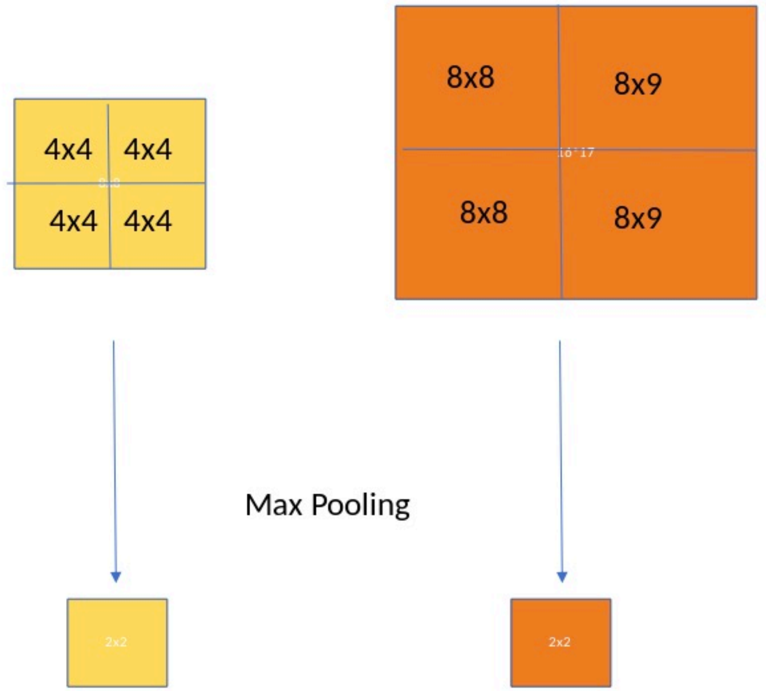
$$L_{smooth}(c_i, \hat{c}_i) = \sum_{j \in \{x,y,w,h\}} smooth_{L_1}(c_{ij} - \hat{c}_{ij})$$

$$smooth_{L_1}(x) = \begin{matrix} 0.5x^2 & |x| < 1 \\ |x| - 0.5 & o.w. \end{matrix}$$

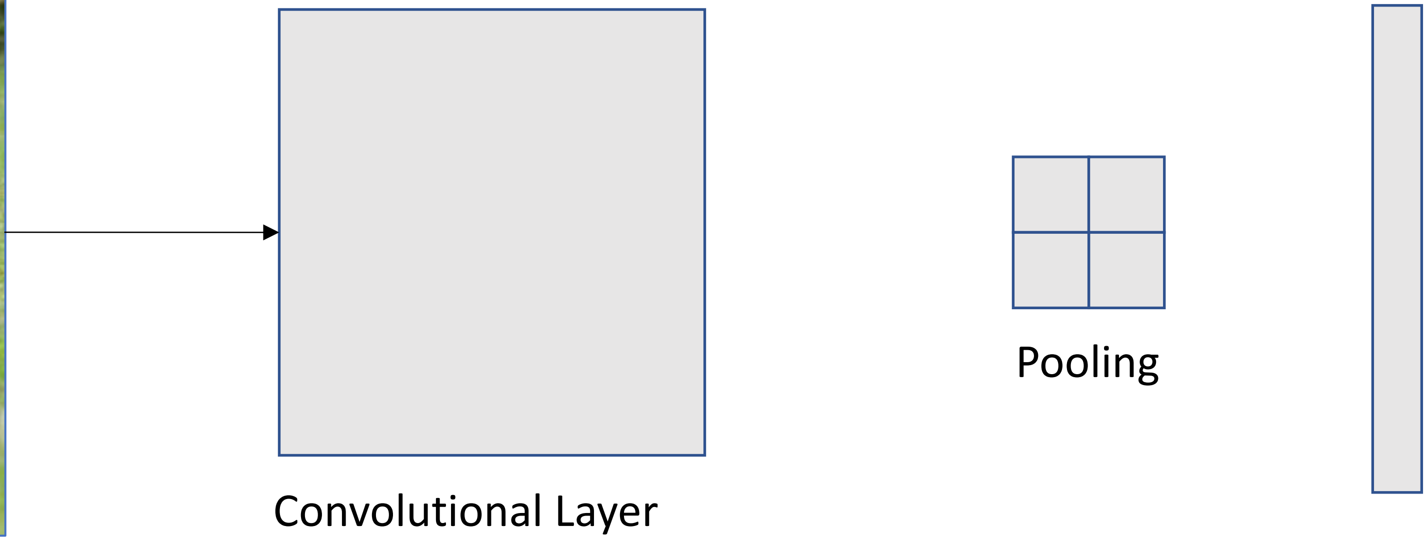


Adaptive Pooling

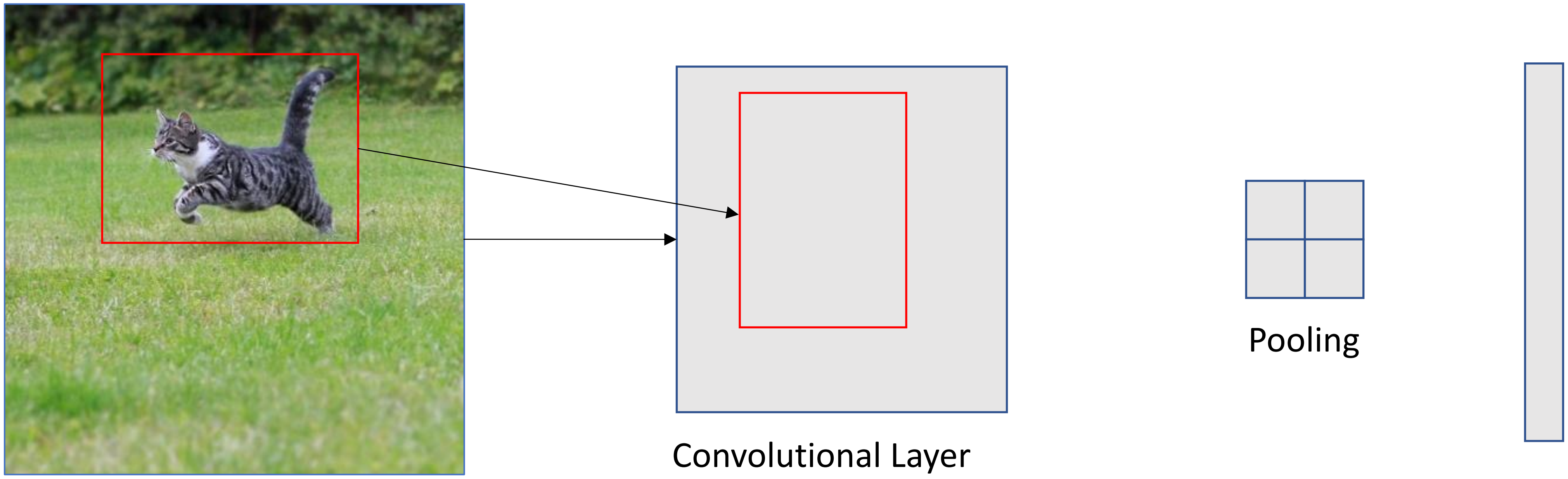
- Adatta la size sull’input per produrre lo stesso output
- Indipendente dalla dimensione della RoI
- Differenziabile
  - Ricordate la regola del gradient router



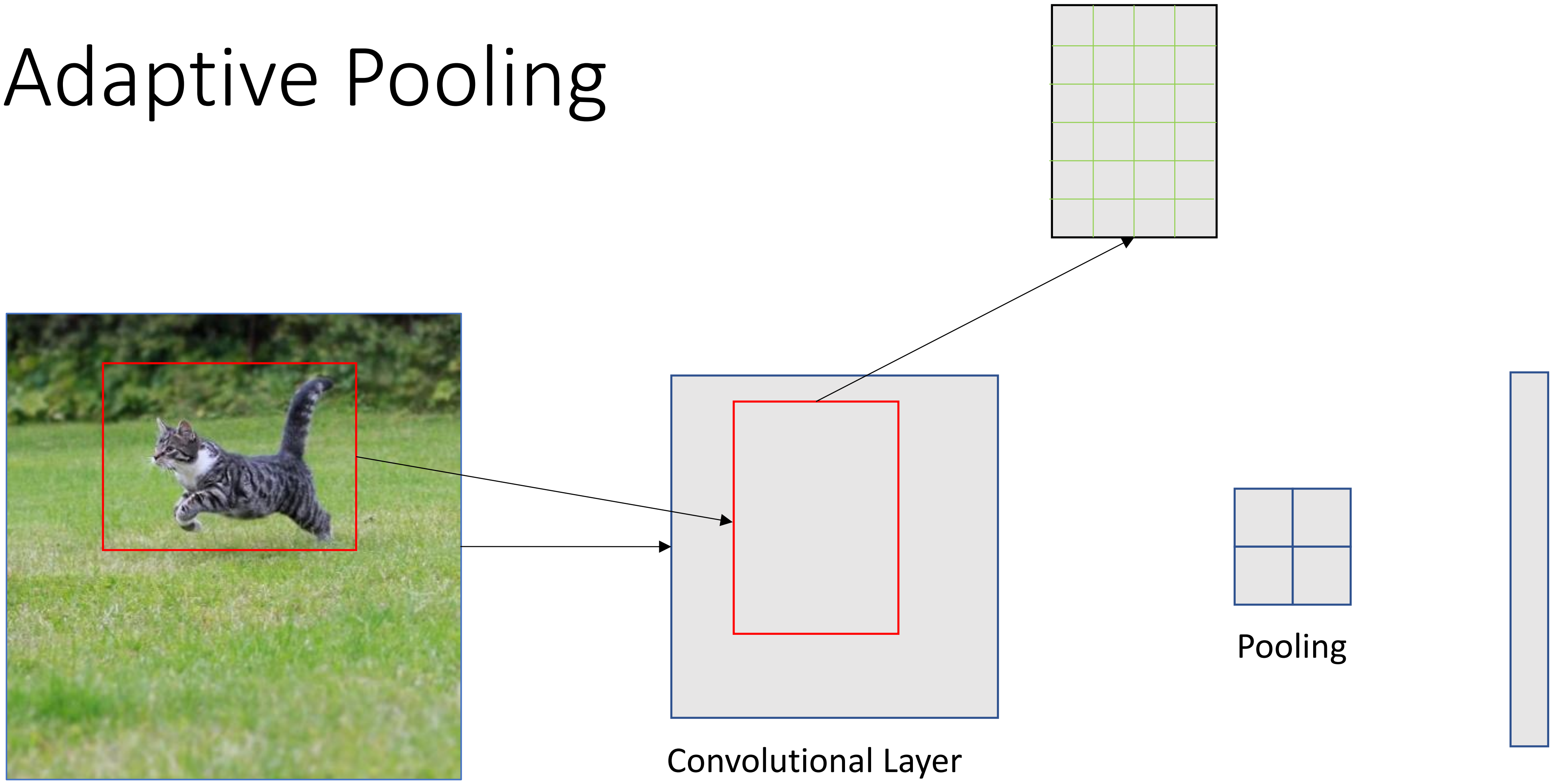
Adaptive Pooling



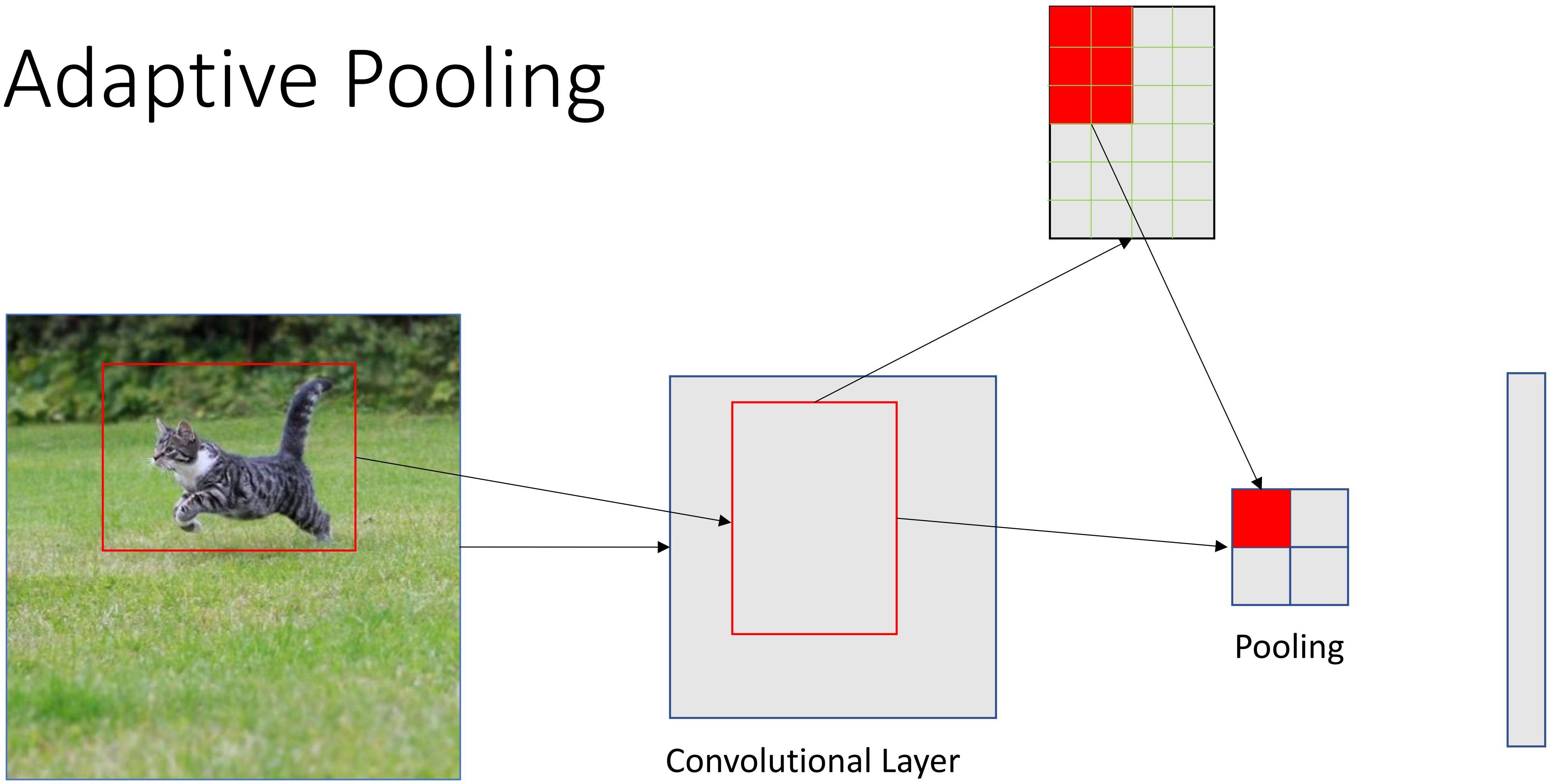
Adaptive Pooling



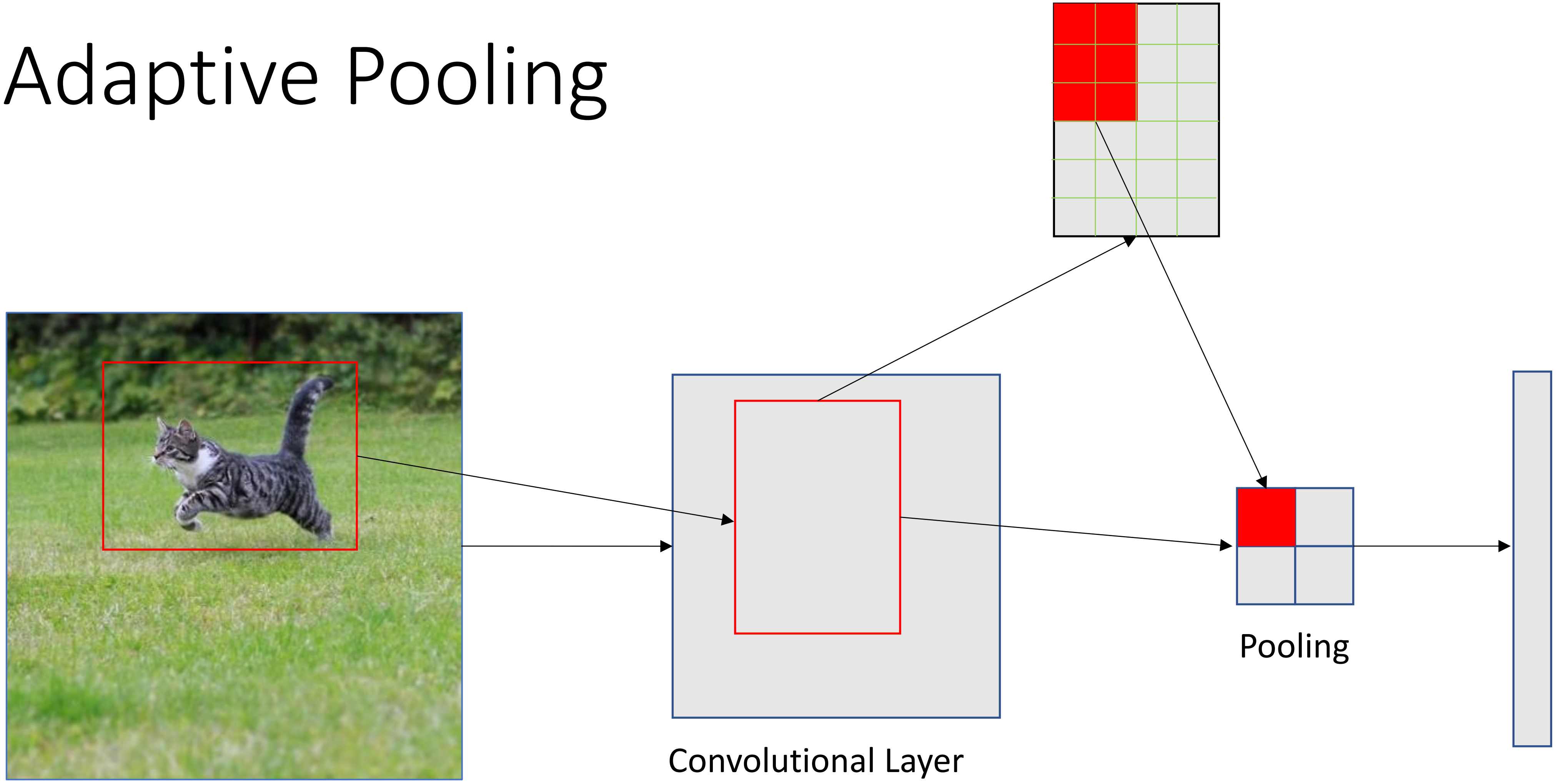
Adaptive Pooling



Adaptive Pooling



Adaptive Pooling

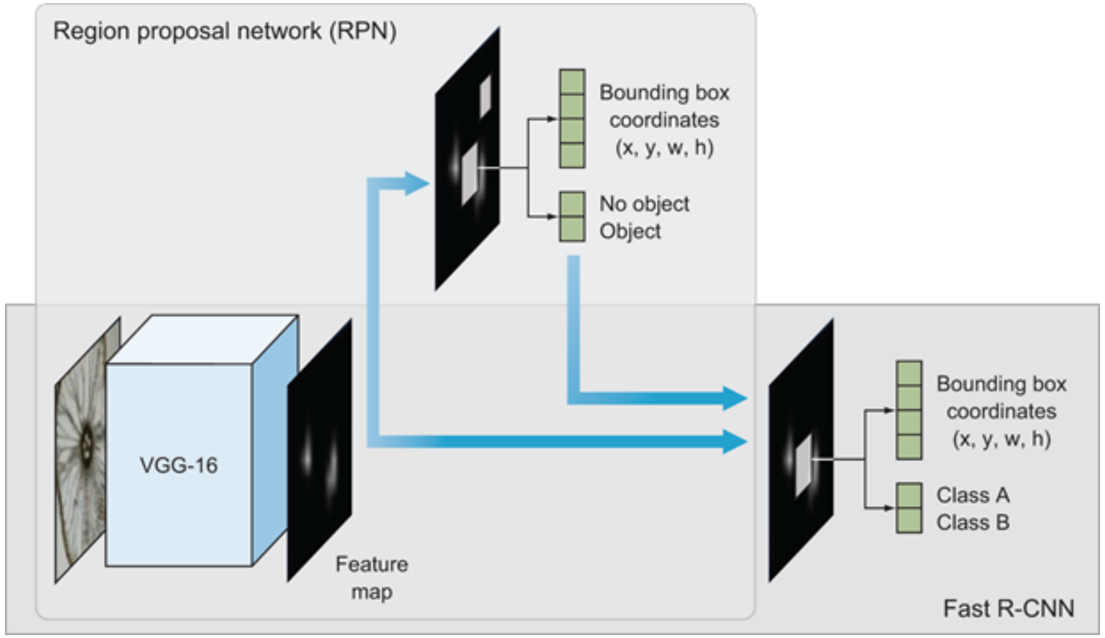


Fast R-CNN

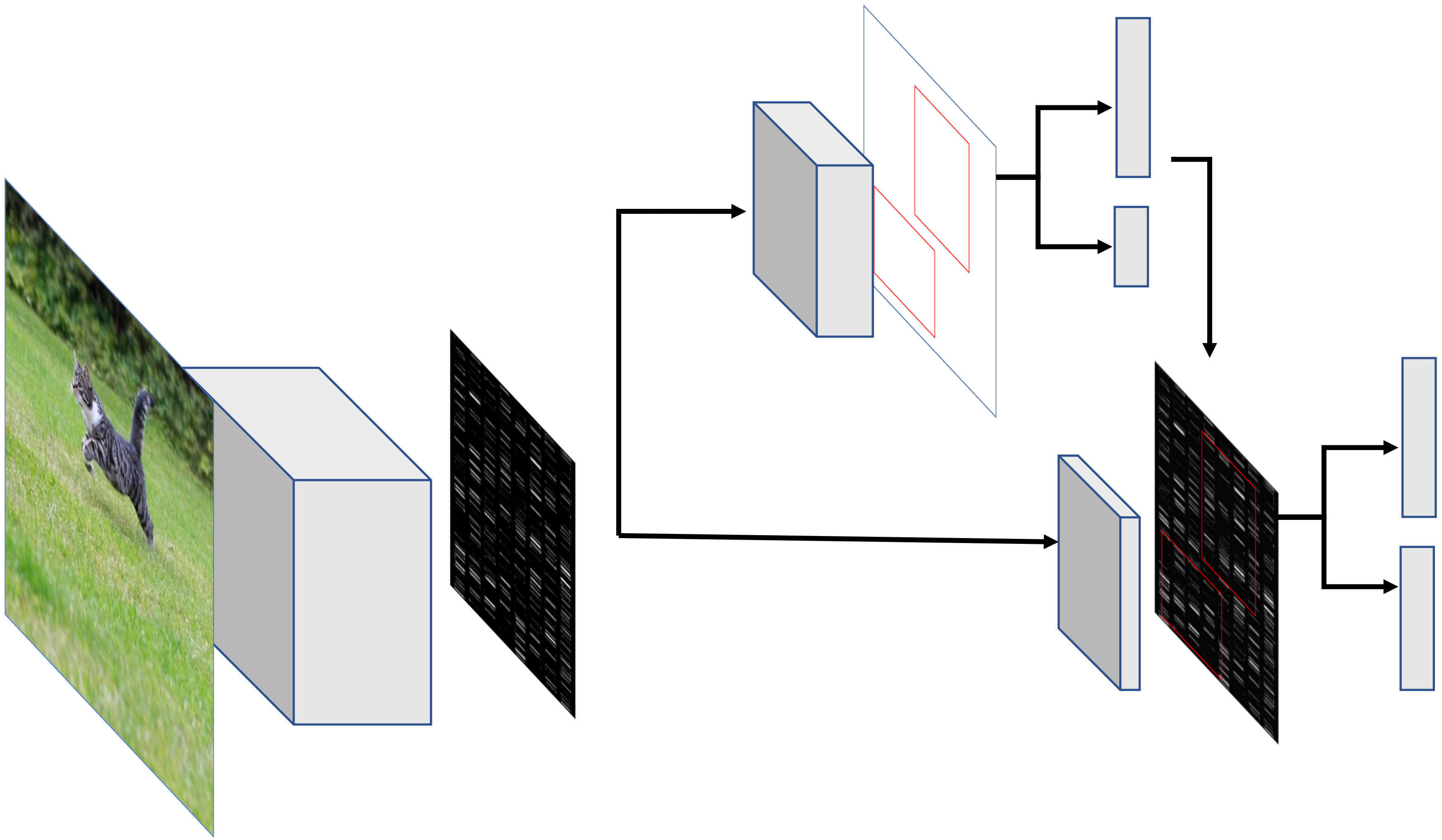
- Vantaggi
    - Architettura integrata
    - Training veloce: speedup 8.8x
    - Predizione veloce
        - 0.32s/image ~ 3FPS
    - mAP 66.9%
- Problemi
    - Le region proposals dipendono ancora dal Selective Search
        - Estremamente lento: 2s/image

Faster R-CNN

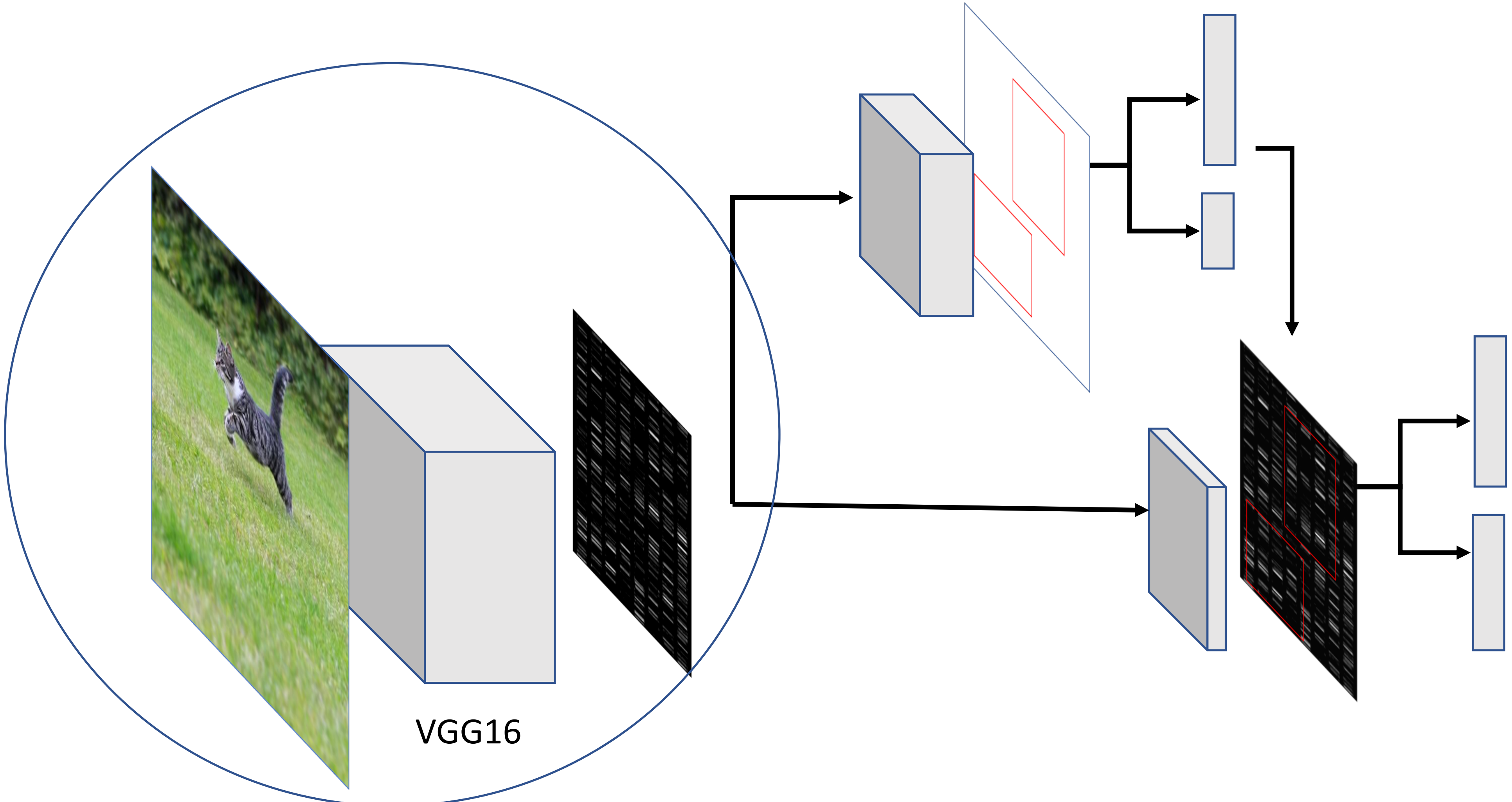
- Girshick et. al, 2016
- Idea: facciamo generare le proposal regions dalla rete stessa
- Due reti a cascata
    - La prima per generare le proposal regions
    - la seconda per la detection



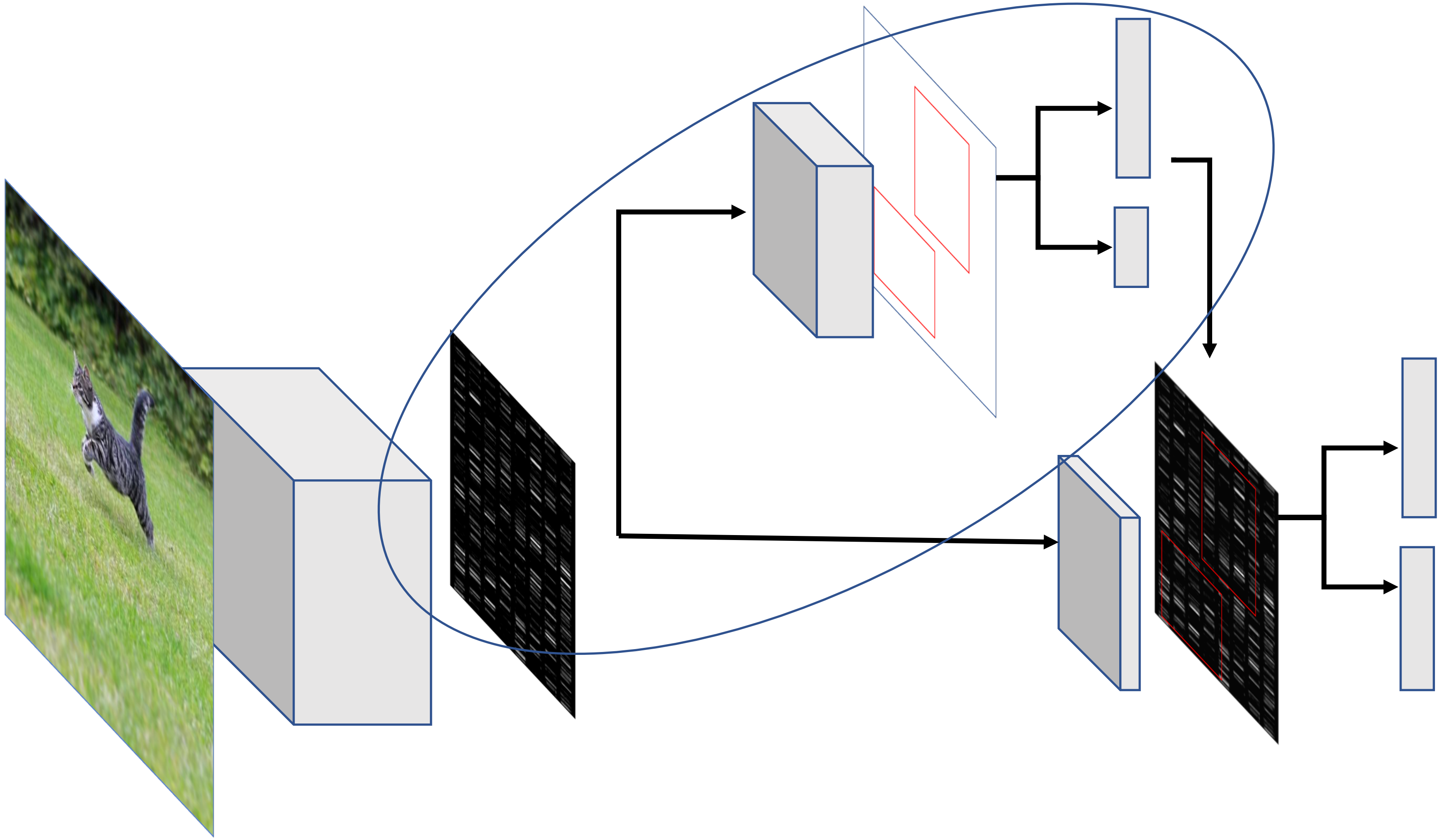
Faster R-CNN



Fase 1: feature extraction



Fase 2: RPN Network



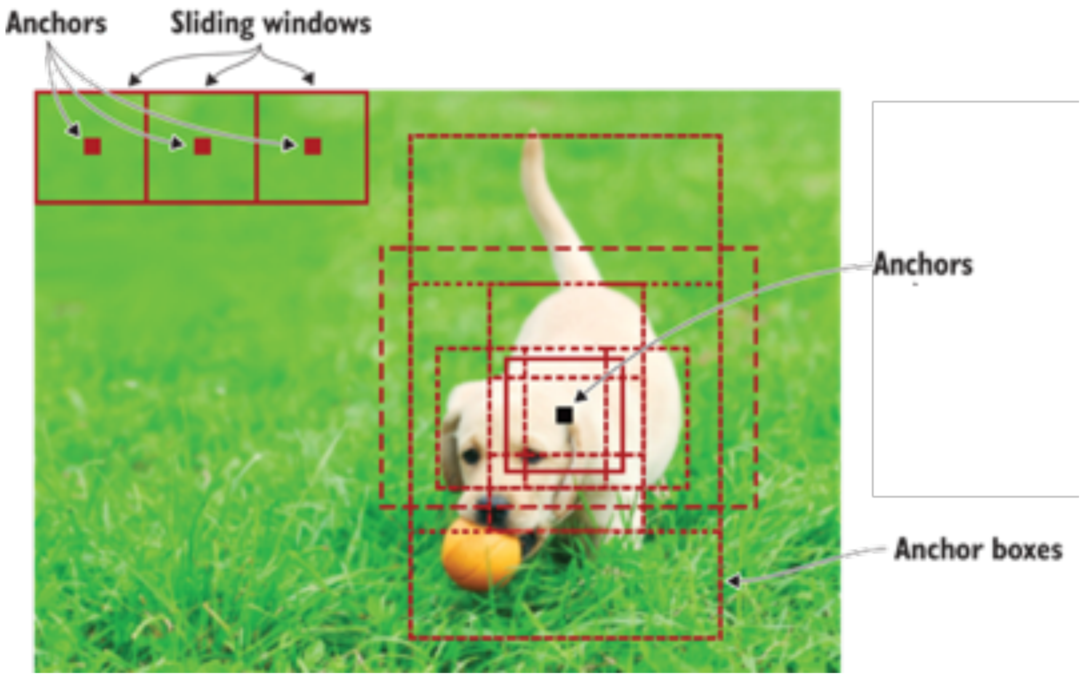
Come vengono generate le Region Proposals?

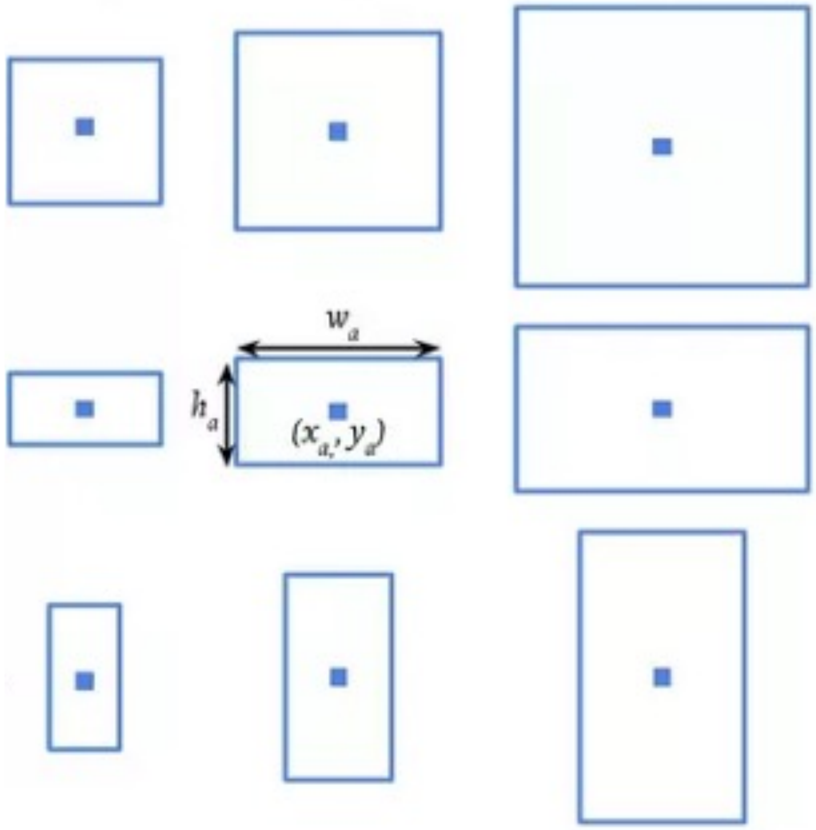
- Anchor boxes (priors)
  - Box di dimensione fissata e precalcolata
- Tre elementi
  - Posizione x, y
  - Scala s
  - Rapporto (aspect ratio) a
- Ogni punto genera una quadrupla (x, y, w, h)

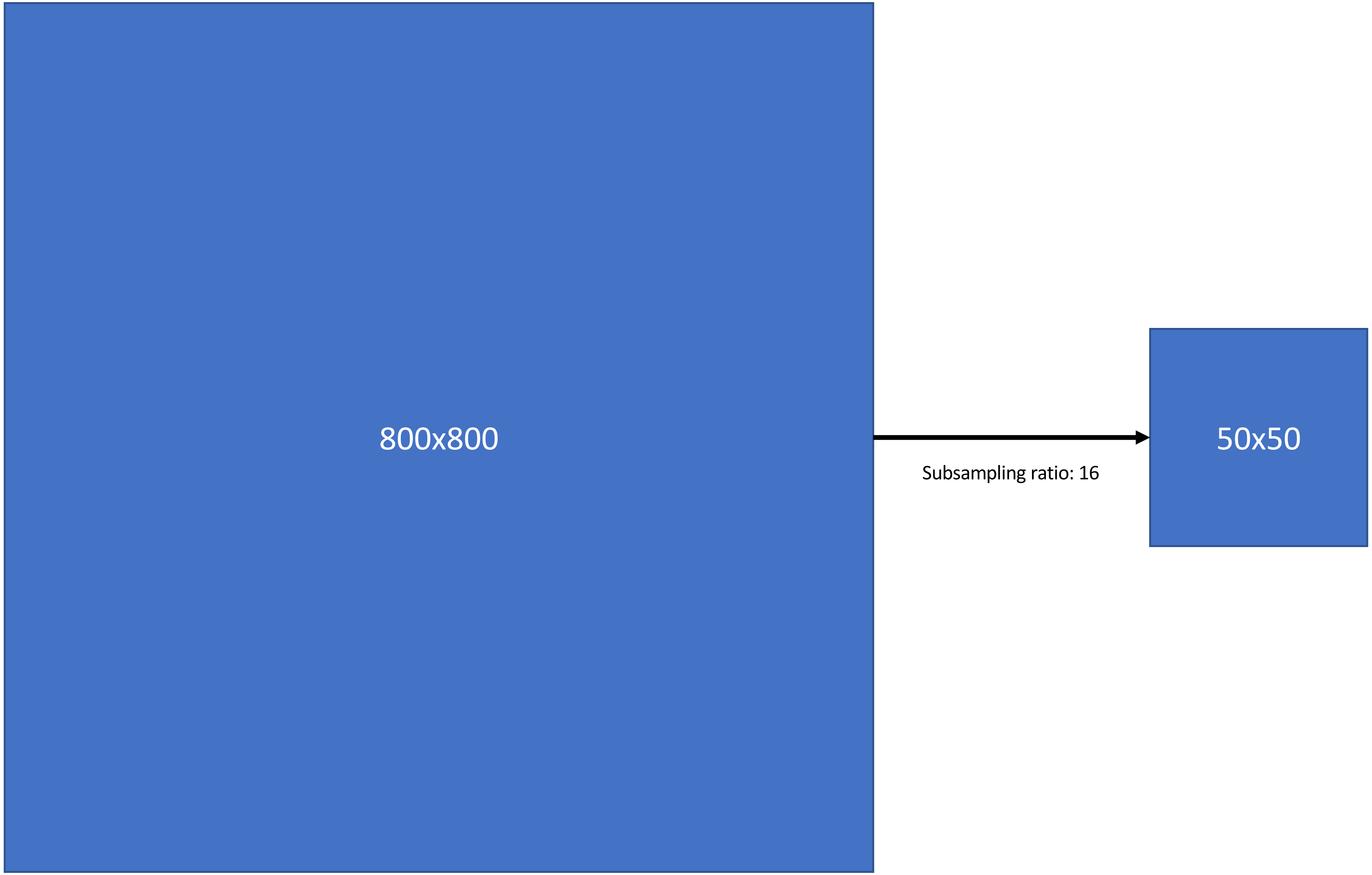
$$w = s \cdot a^2$$
$$h = \frac{s}{a}$$

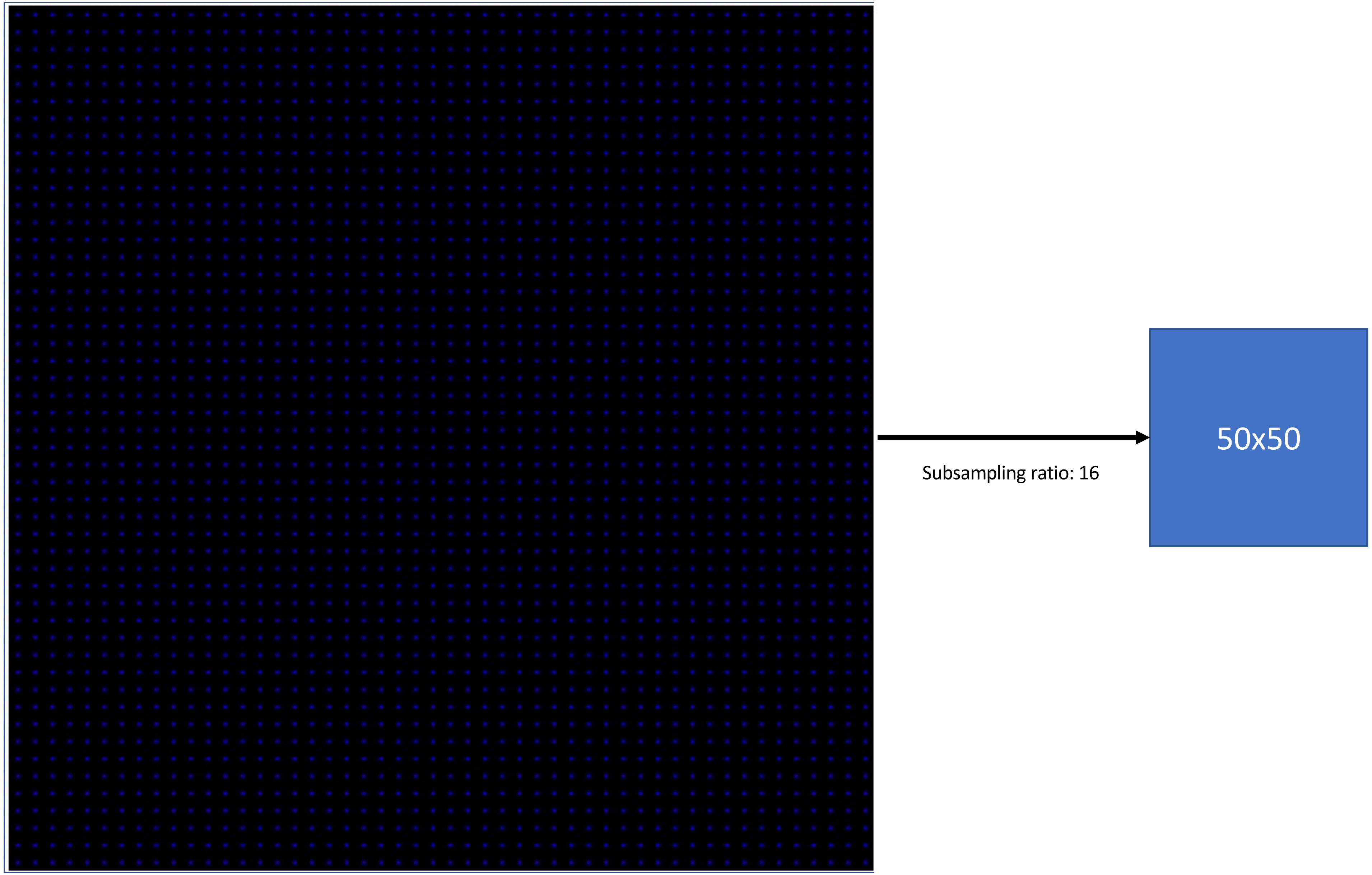
Come vengono generate le Region Proposals?

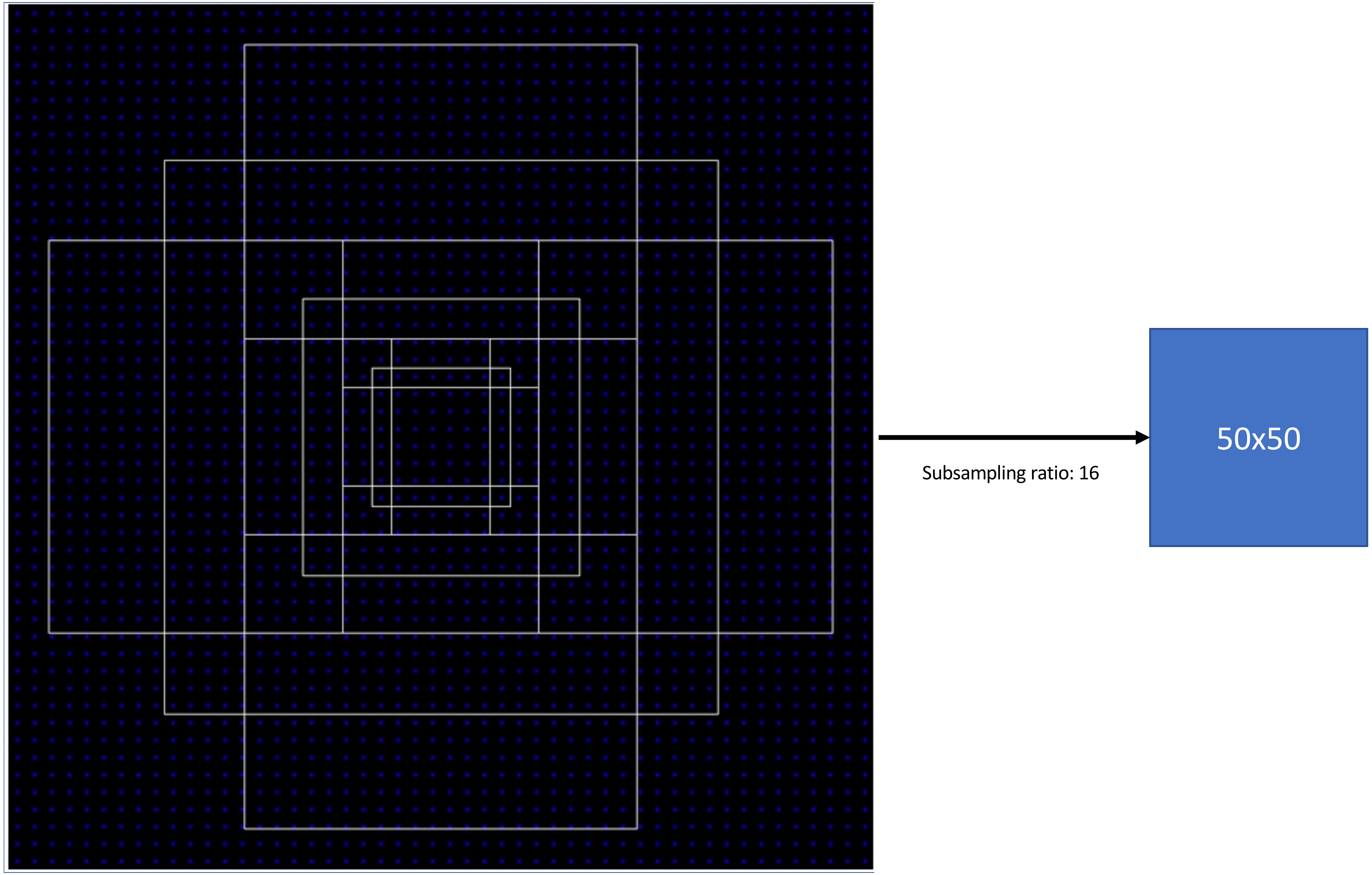
- $s = [0.5,1,2]$
- a=[1:1,1:2,2:1]

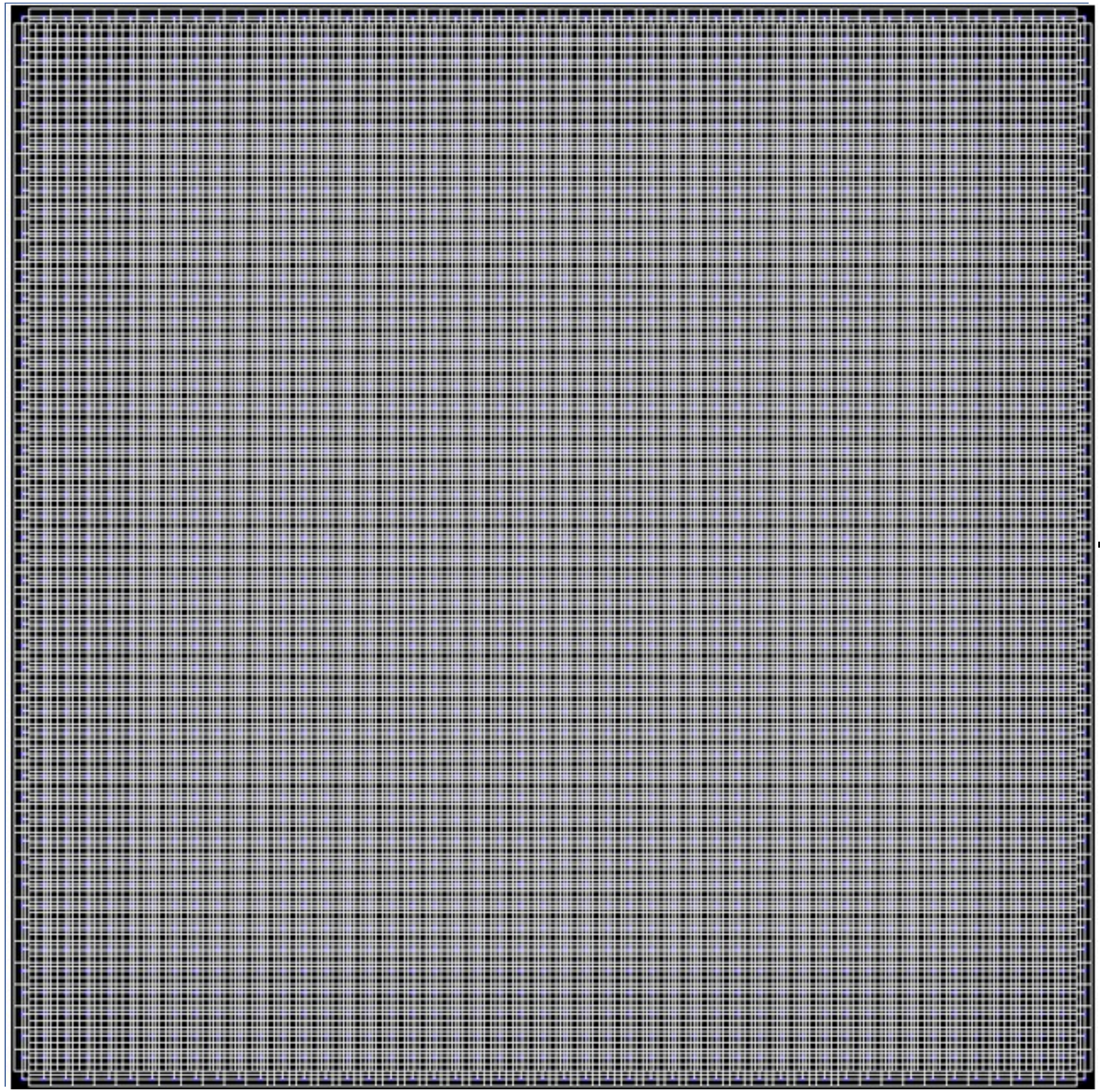


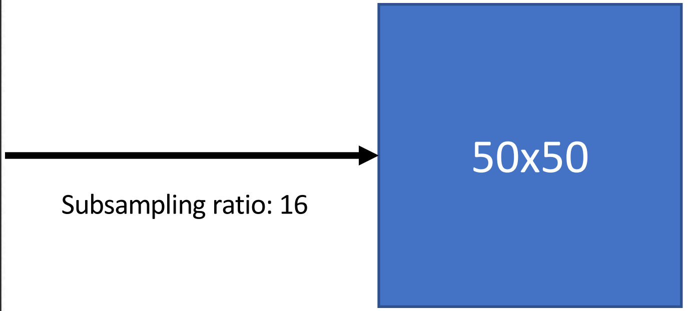



800x800
Subsampling ratio: 16
50x50

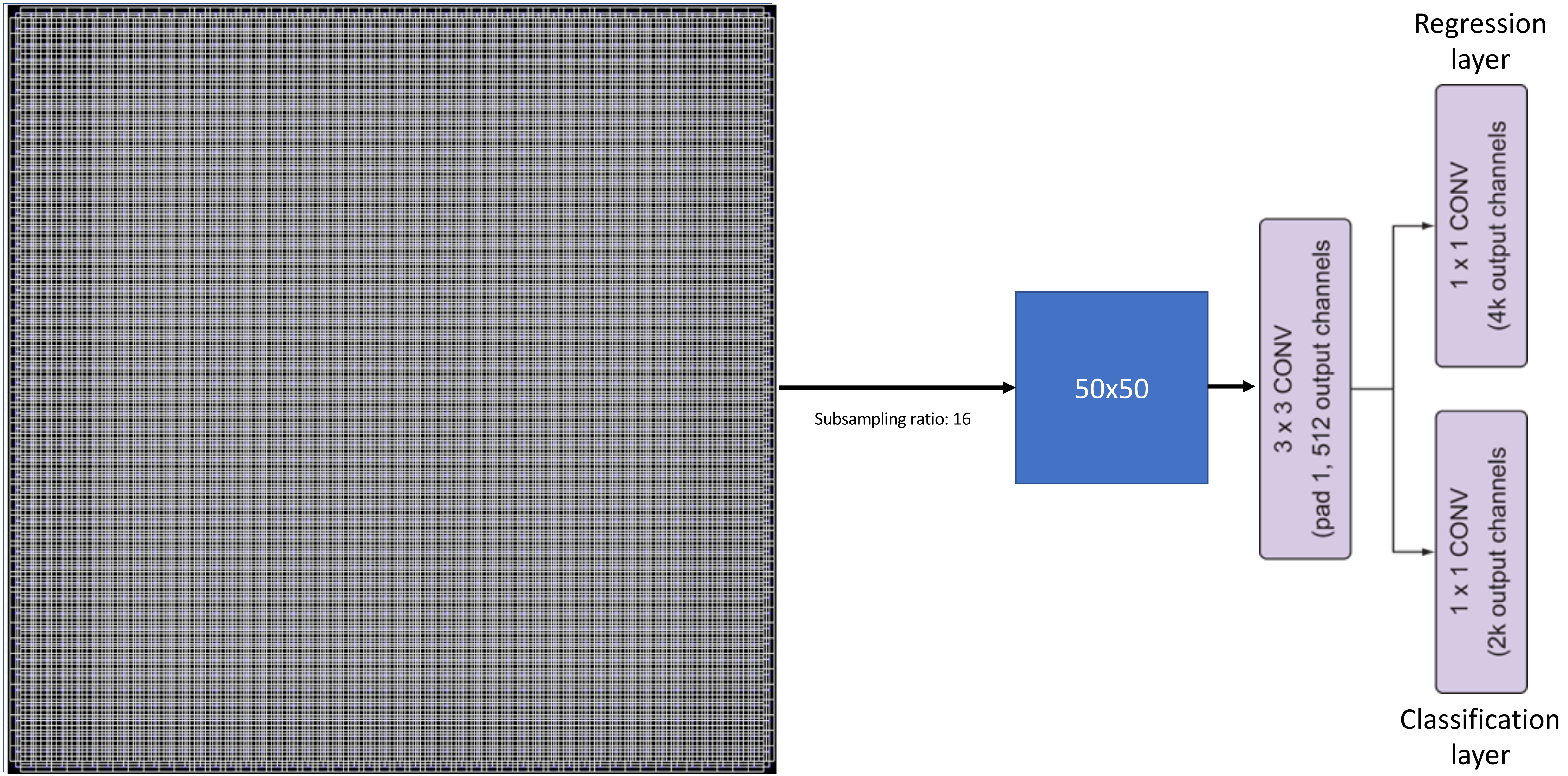

Subsampling ratio: 16
50x50


Subsampling ratio: 16
50x50





- Ogni cella della feature map individua k anchor boxes sull'immagine orginale
- Totale anchor boxes: $k \cdot W \cdot H$
  - dove W, H è la size della feature map


Regression layer
Subsampling ratio: 16
50x50
3 x 3 CONV
(pad 1, 512 output channels
1 x 1 CONV
(4k output channels
1 x 1 CONV
(2k output channels
Classification layer

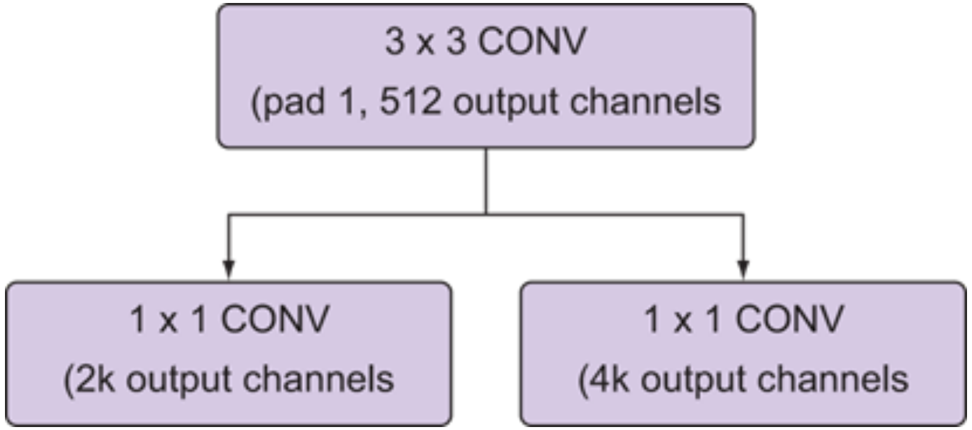
RPN in Pytorch

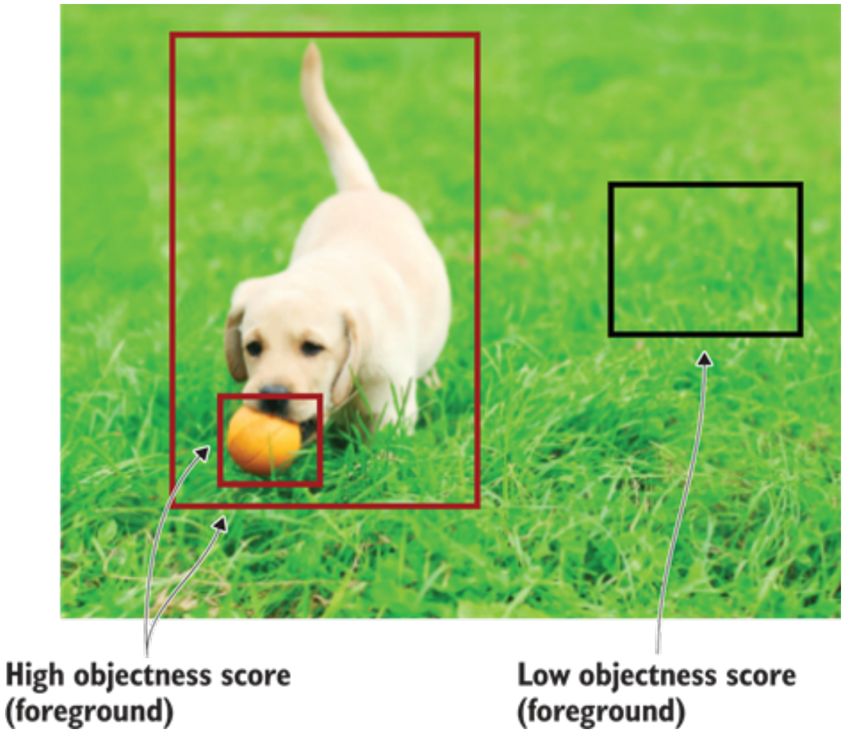
```
class RPN(nn.Module):
    def __init__(self,in_channels = 512, mid_channels = 512, n_anchor = 9):
        super(RegioProposalNetwork, self).__init__()

        conv1 = nn.Conv2d(in_channels, mid_channels, 3, 1, 1)
        nn.init.normal(conv1.weight, mean=0, std=0.001)
        nn.init.zeros(conv1.bias)

        reg_layer = nn.Conv2d(mid_channels, n_anchor *4, 1, 1, 0)
        nn.init.normal(reg_layer.weight, mean=0, std=0.001)
        nn.init.zeros(reg_layer.bias)

        cls_layer = nn.Conv2d(mid_channels, n_anchor *2, 1, 1, 0)
        nn.init.normal(cls_layer.weight, mean=0, std=0.001)
        nn.init.zeros(cls_layer.bias)


    def forward(self, x):
        x = conv1(x)
        pred_anchor_locs = reg_layer(x)
        pred_cls_scores = cls_layer(x)

        pred_anchor_locs = pred_anchor_locs.permute(0, 2, 3, 1).contiguous().view(1, -1, 4)
        pred_cls_scores = pred_cls_scores.permute(0, 2, 3, 1).contiguous()

        pred_cls_scores  = pred_cls_scores.view(pred_cls_scores.shape[0], -1, 2)

        return pred_anchor_locs, pred_cls_scores
```

Classification, regression

- Un anchor box è positivo se ha un $IoU > 0.7$ con un oggetto
    - e negativo se ha un $IoU < 0.3$

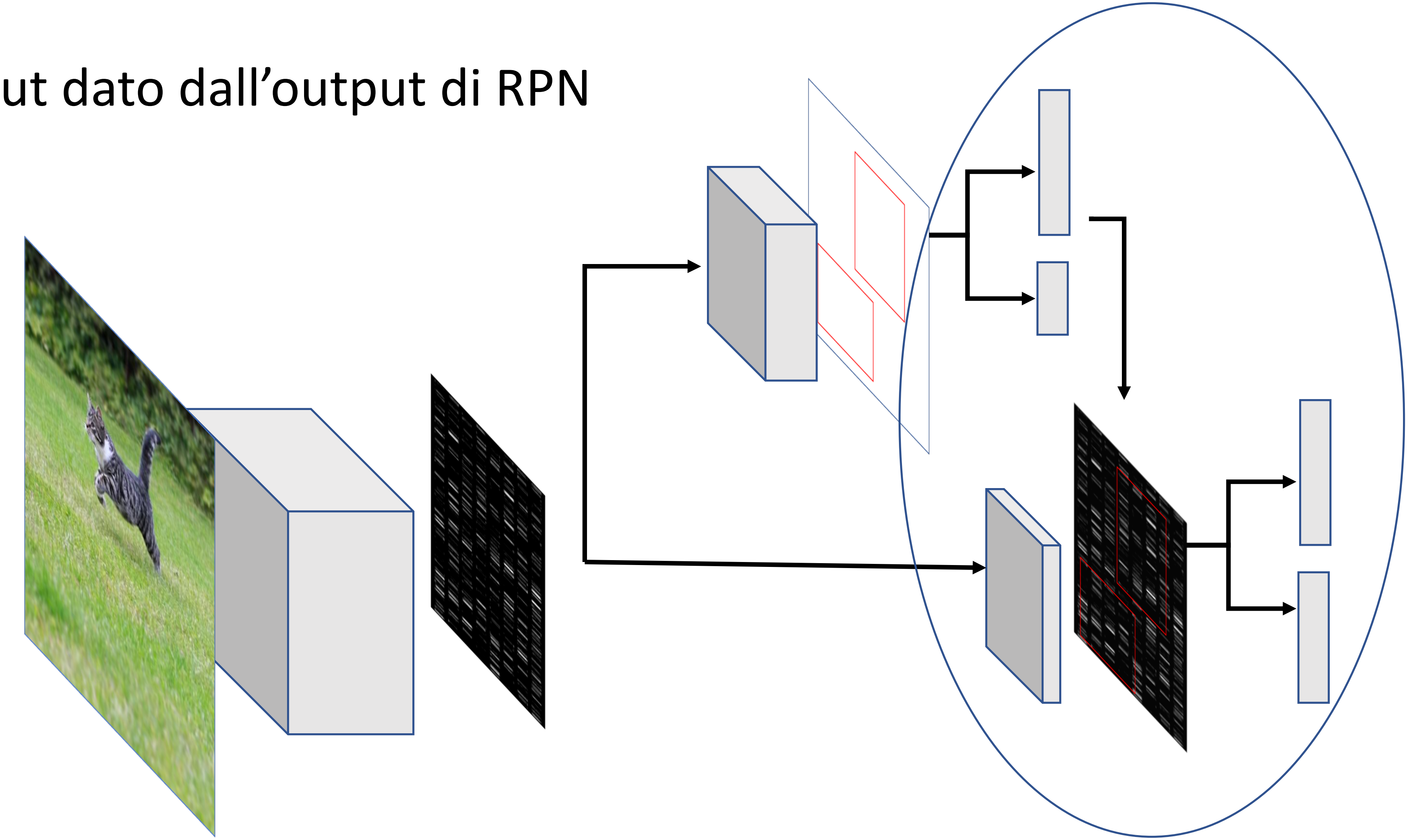
$$loss = \sum_i L_{cls}\,(\hat{p}_i, y_i) + \sum_i L_{reg}(\hat{c}_i, c_i)$$





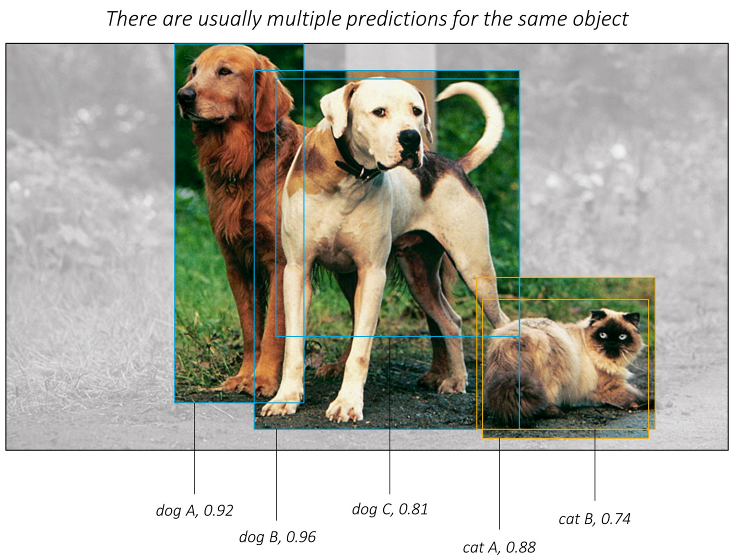
Fase 3: Fast R-CNN

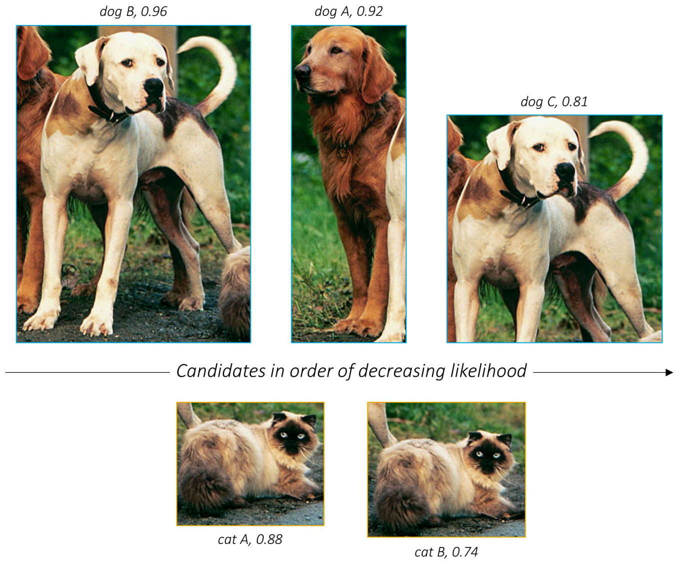
- Input dato dall'output di RPN

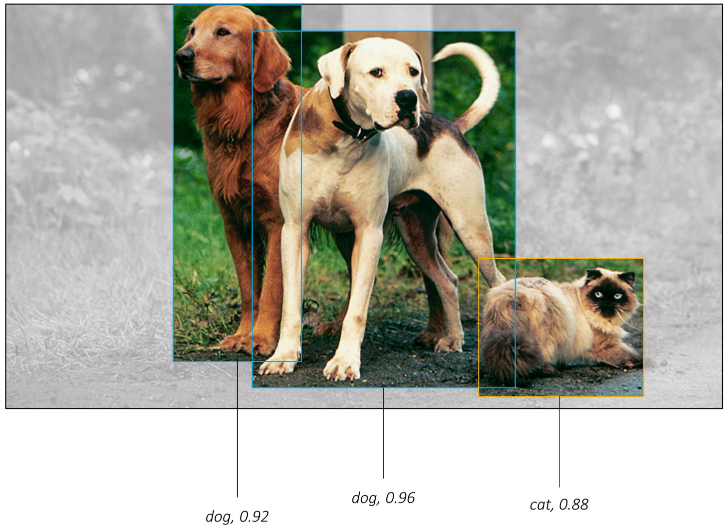


Postprocessing: Non-Maximum Suppression

- Si ordinano le regioni per score di classificazione
- Ogni box rimuove tutti i box della stessa classe che lo seguono e che hanno $IoU > 0.5$







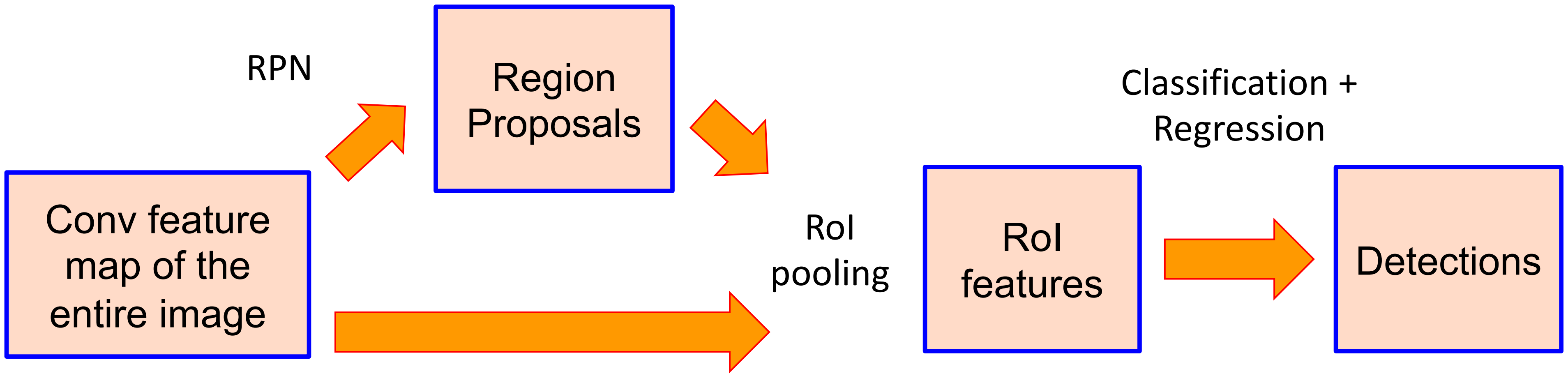
Riassunto

Metodo	Sec/image (FPS)	Speedup	mAP
R-CNN	~50s (0,02)	1x	66%
Fast R-CNN	~2s (0,5)	25x	66,9%
Faster R-CNN	~0,2s (5-7)	250x	69,9%

- Addestramento troppo lento
- Fasi multiple
- Può supportare real-time object detection?
  - No
  - Troppo lenti

Evoluzione

- Multi-stage object detectors



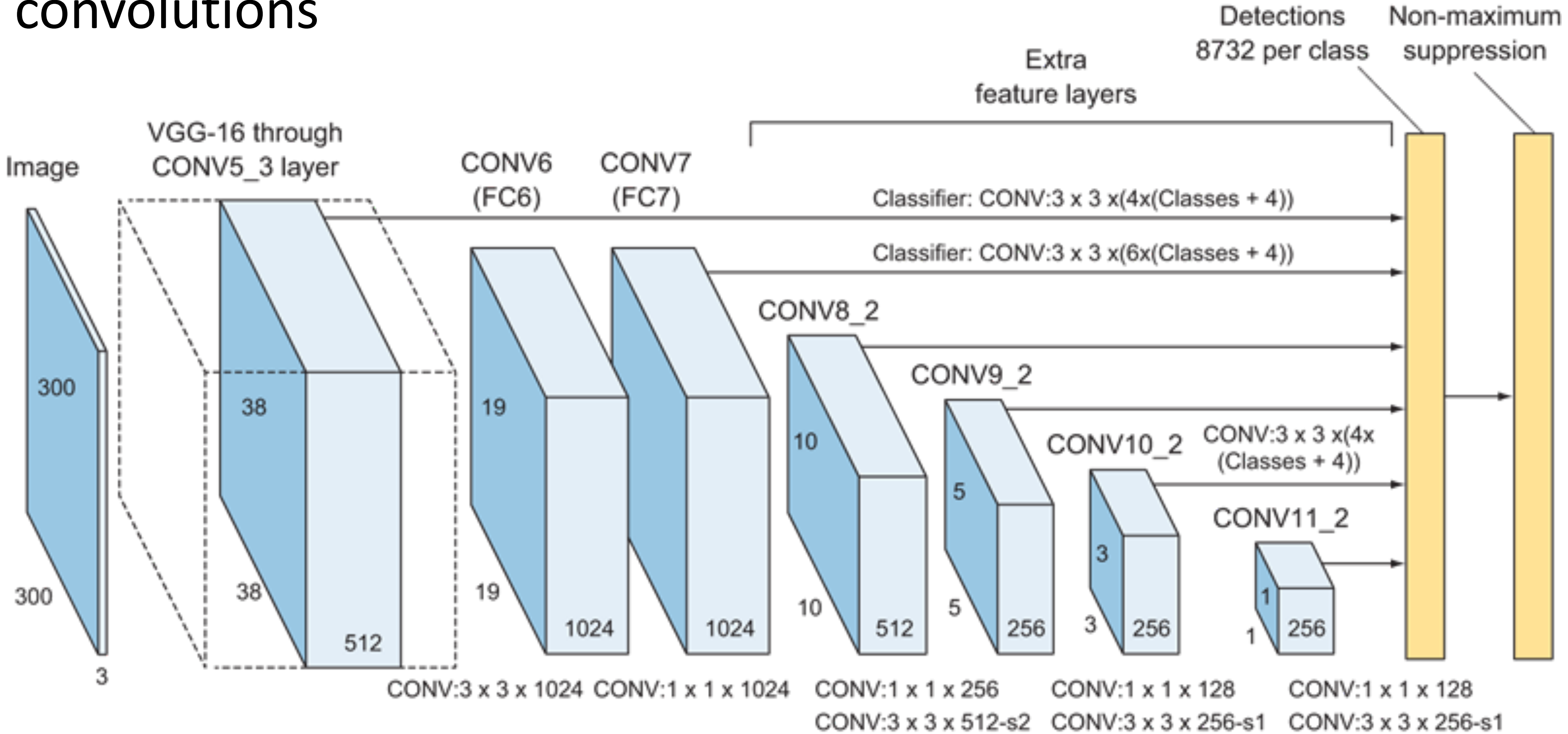
- Single-shot object detectors

SSD: Single-Shot MultiBox Detector

- Szegedy et al., 2016
- 74% mAP, 59 FPS
- Principali caratteristiche
  - Eliminazione delle region proposals
  - Rete di base (preaddestrata) per estrarre le feature maps.
  - Multi-scale feature layers
    - Una serie di filtri convoluzionali in cascata
    - Riducono la dimensione e abilitano la detection su scale multiple
  - Non-maximum suppression

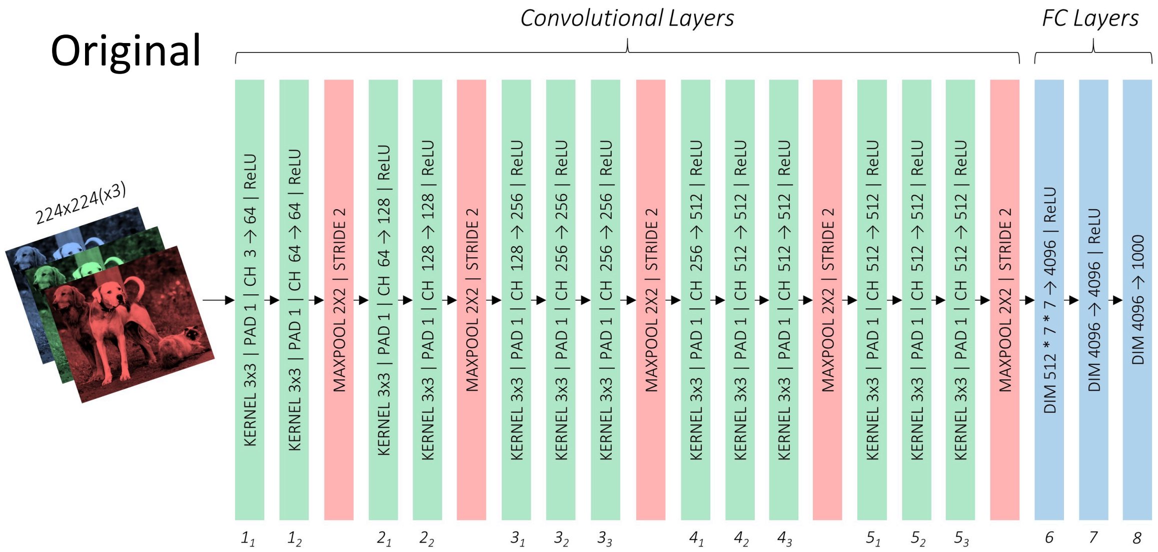
SSD

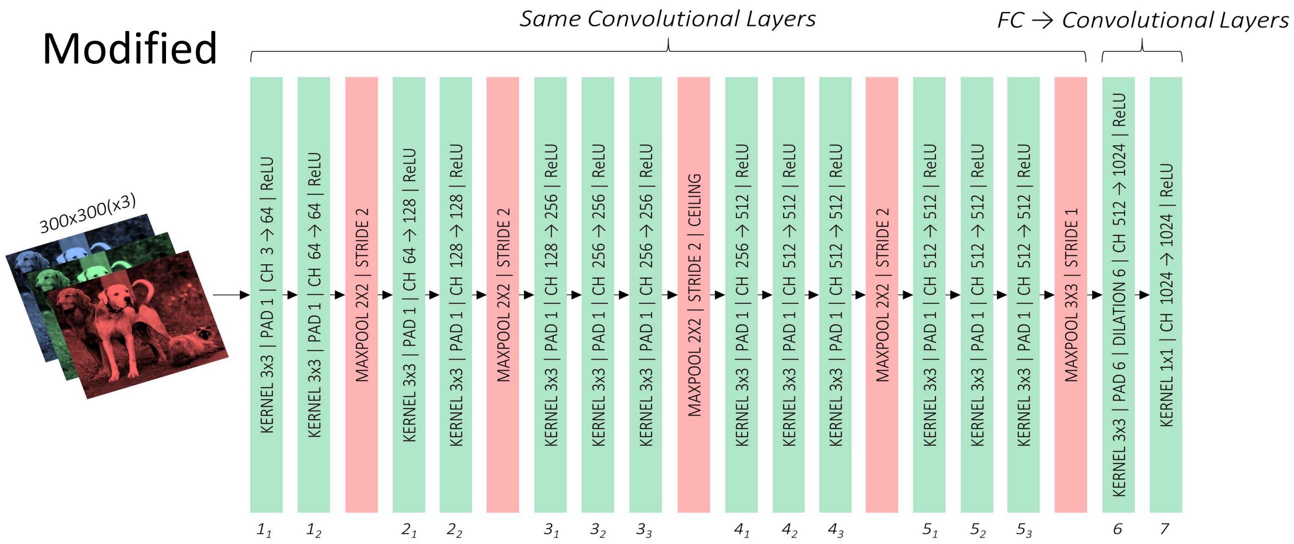
- Tre componenti
  - Base convolutions
  - Auxiliary convolutions
  - Prediction convolutions



SSD – Base convolutions

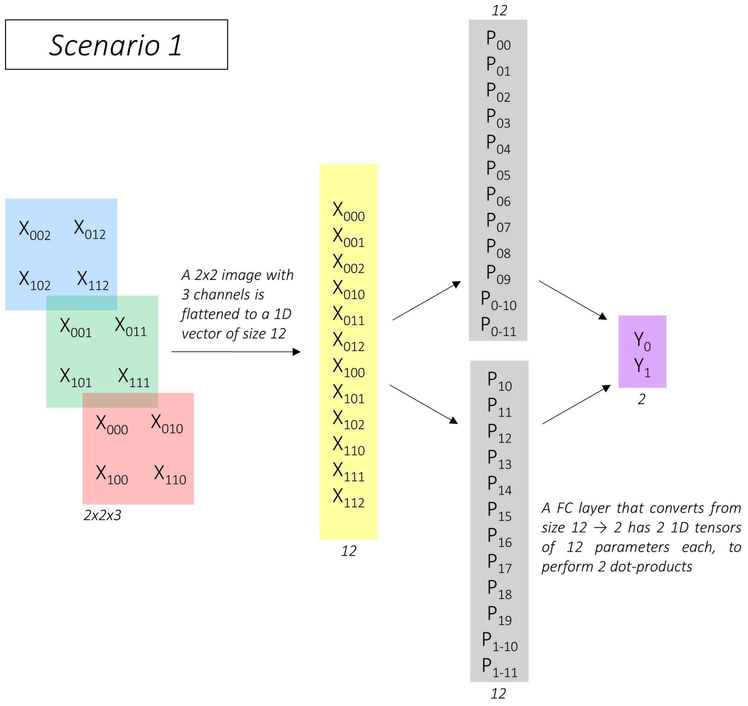
- Modified VGG-16
  - Input size: 300x300
  - Modifichiamo il quinto pooling layer
  - Rimuoviamo FC8, ristrutturiamo FC6, FC7 (convolutionize, reduce channels, subsample->decimazione/dilation)

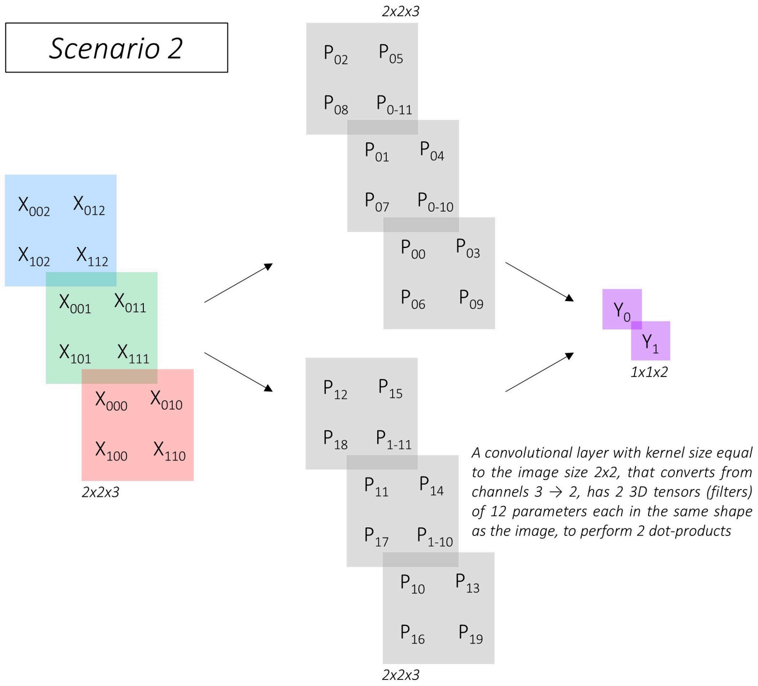




SSD – Base convolutions

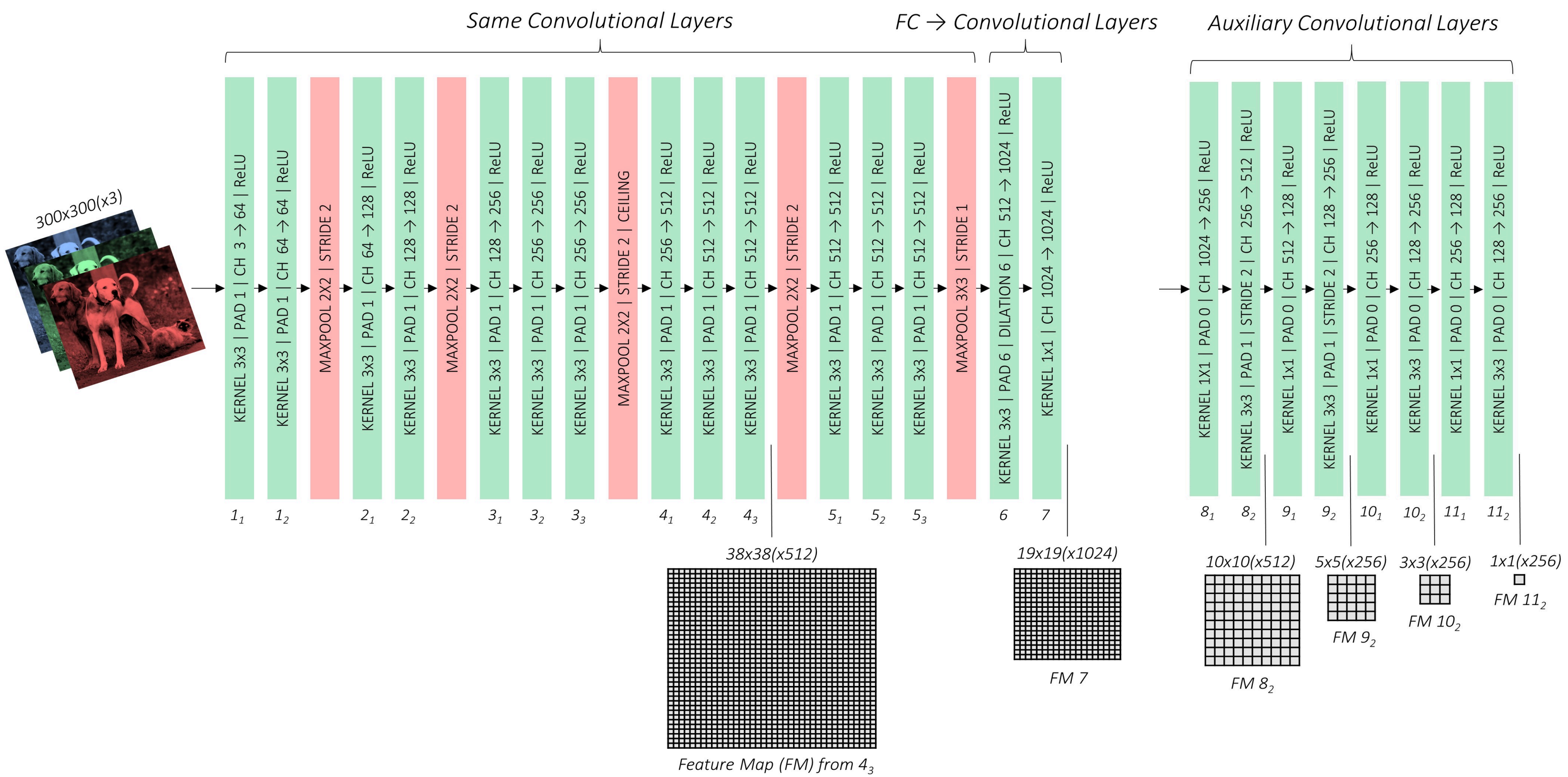
- Reshaping
  - Su un’immagine di dimensione H, W su I canali, un FC con output N equivale a un CONV con kernel HxW e N canali di output





SSD – Auxiliary convolutions

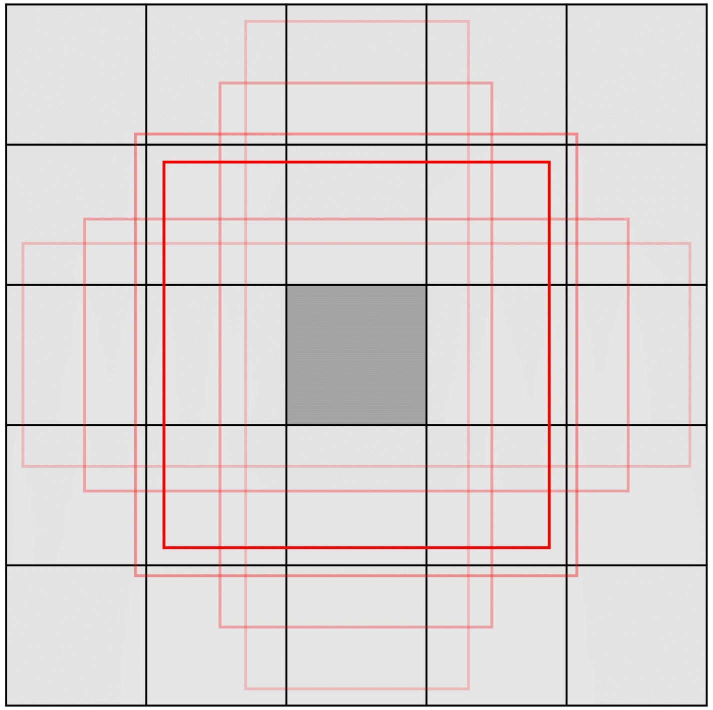
- Quattro nuovi blocchi
  - Ogni blocco produce una Feature Map di output



SSD – Prediction outputs

- Cosa rappresentano gli FM di output?
  - Celle su cui definire i priors

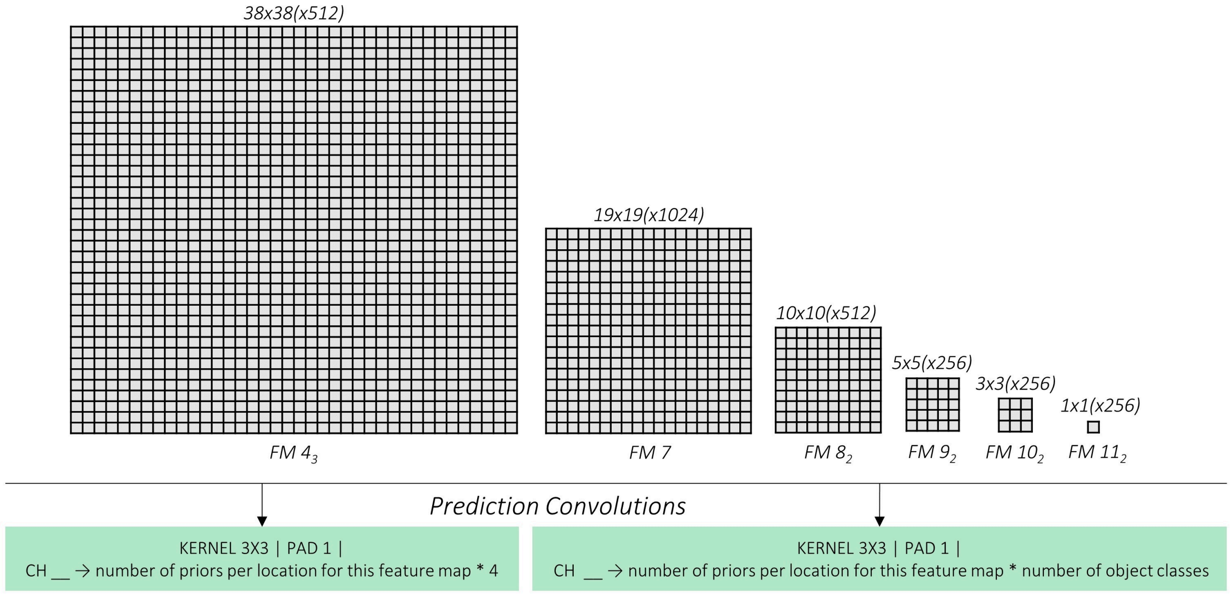
FM 9_2



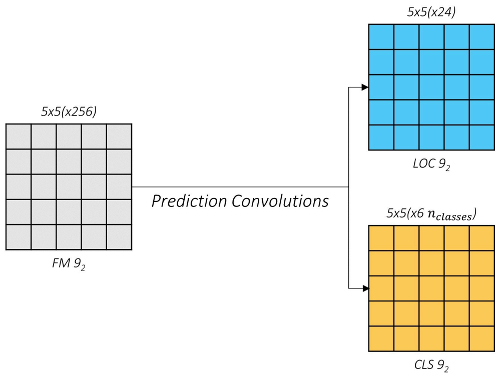
Feature Map From	Feature Map Dimensions	Prior Scale	Aspect Ratios	Number of Priors per Position	Total Number of Priors on this Feature Map
`conv4_3`	38, 38	0.1	1:1, 2:1, 1:2 + an extra prior	4	5776
`conv7`	19, 19	0.2	1:1, 2:1, 1:2, 3:1, 1:3 + an extra prior	6	2166
`conv8_2`	10, 10	0.375	1:1, 2:1, 1:2, 3:1, 1:3 + an extra prior	6	600
`conv9_2`	5, 5	0.55	1:1, 2:1, 1:2, 3:1, 1:3 + an extra prior	6	150
`conv10_2`	3, 3	0.725	1:1, 2:1, 1:2 + an extra prior	4	36
`conv11_2`	1, 1	0.9	1:1, 2:1, 1:2 + an extra prior	4	4
Grand Total	–	–	–	–	**8732 priors**

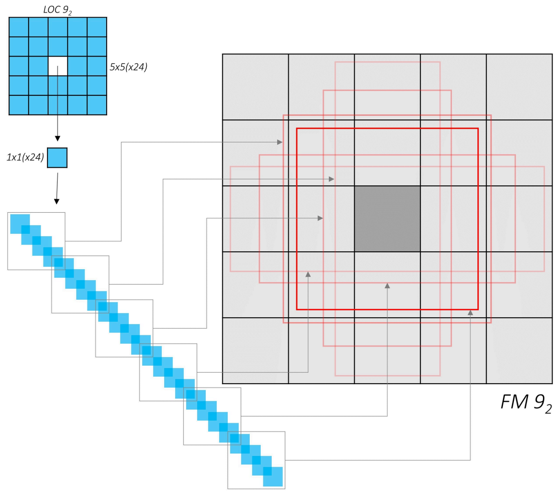
SSD - Prediction convolutions

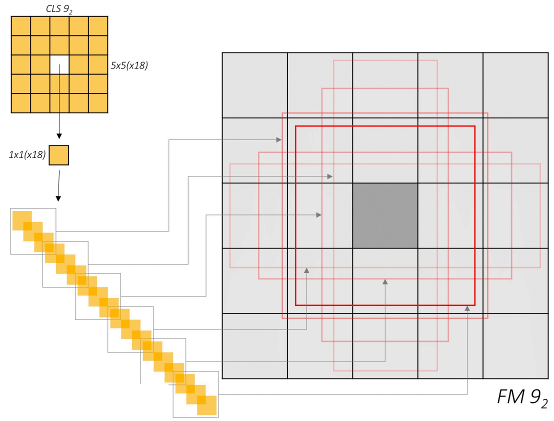
- Ogni prior su ogni posizione di ogni feature map produce una predizione
- Due layer convoluzionali
  - Localization layer $3 \times 3 \times 4$
    - Regressione su $\left(g_{c_x}, g_{c_y}, g_w, g_h\right)$
  - Classification layer $3 \times 3 \times n_{classes}$



SSD – Prediction Convolutions







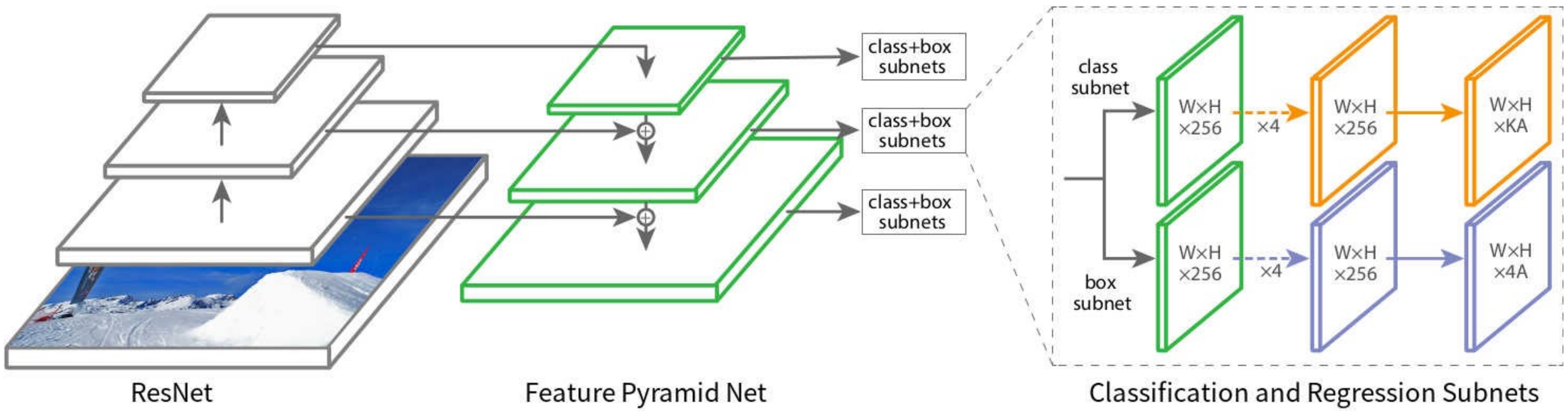
SSD - Riassunto

- Training tips
  - Hard negative mining: rapporto positivi/negativi 1 a 3
  - Data augmentation
  - Transfer learning: Atrous convolution: decimazione/dilation dei kernel su FC6
- Due varianti
  - SSD300
  - SSD512

Metodo	FPS	mAP	Priors
Faster R-CNN	5-7	69,9%	~6000
SSD300	46	74.3%	8732
SSD512	19	76,8%	24564

RetinaNet

- Feature Pyramids
  - Estende il concetto di multi-scale anchor boxes
- Focal loss

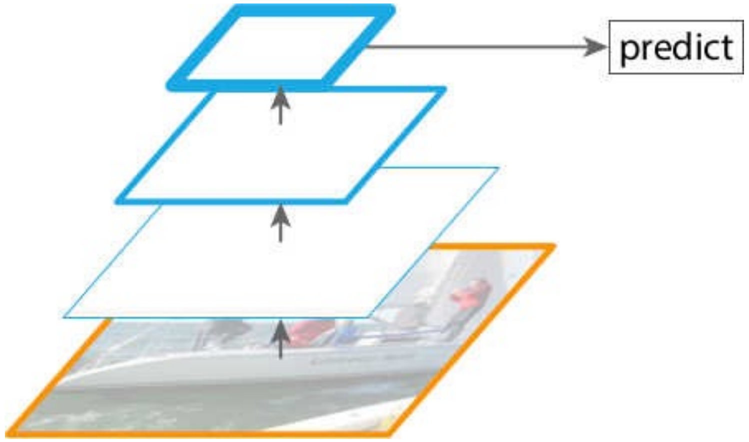


RetinaNet: architettura

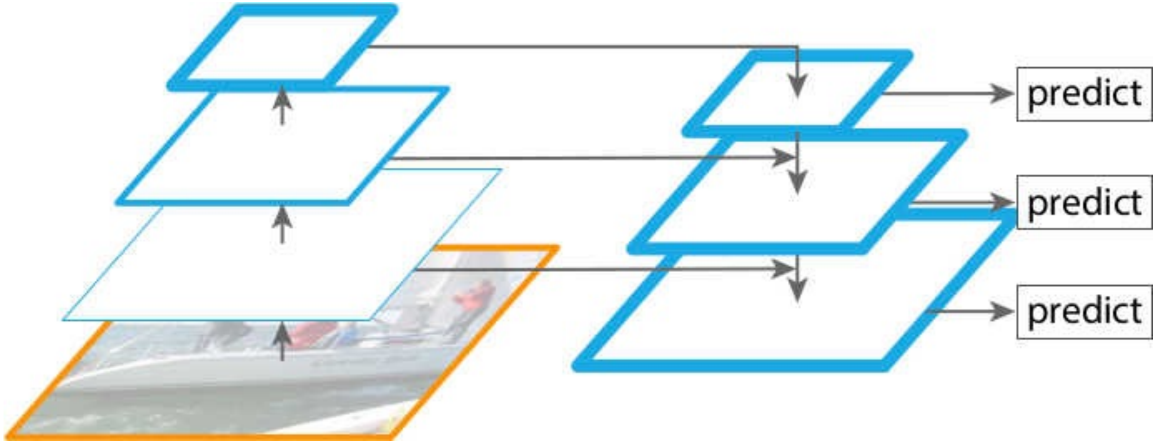
- Tre componenti
  - ResNet come architettura base
  - Feature Pyramid Network per combinare i risultati
  - Una sottorete per BB Regression e Classification

Feature Pyramid Network

- In una rete convoluzionale, l’ultima feature map è la più significativa
- Idea: combiniamo l’informazione di tale feature map con quella dei layer inferiori
  - Upsample e combinazione
  - Predizione su ogni layer: le feature maps possono essere usate indipendentemente e rendono il modello scale-invariant



Original

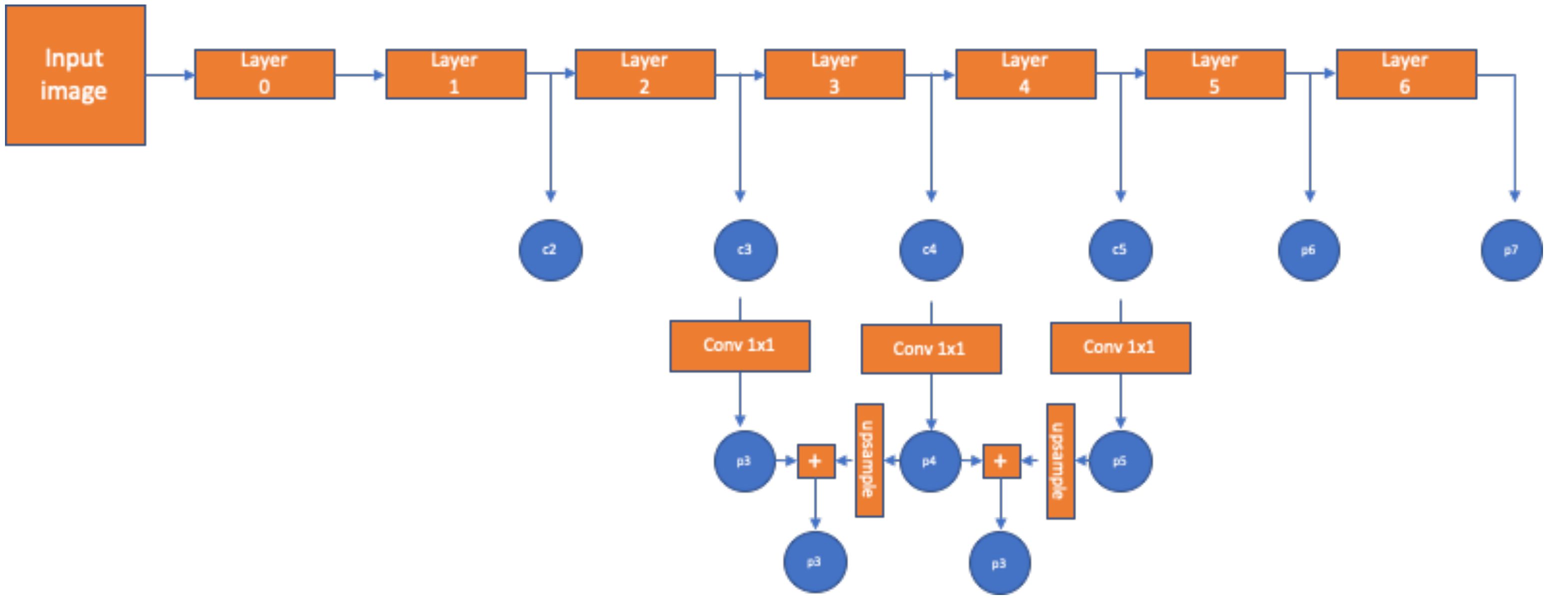


Feature Pyramid

Architettura finale

- Anchor points
  - SSD ~10K
  - RetinaNet ~ 100K

```python
def forward(self, x):
    # Bottom-up
    c1 = F.relu(self.bn1(self.conv1(x)))
    c1 = F.max_pool2d(c1, kernel_size=3, stride=2, padding=1)
    c2 = self.layer1(c1)
    c3 = self.layer2(c2)
    c4 = self.layer3(c3)
    c5 = self.layer4(c4)
    p6 = self.conv6(c5)
    p7 = self.conv7(F.relu(p6))
    # Top-down
    p5 = self.latlayer1(c5)
    p4 = self._upsample_add(p5, self.latlayer2(c4))
    p4 = self.toplayer1(p4)
    p3 = self._upsample_add(p4, self.latlayer3(c3))
    p3 = self.toplayer2(p3)
    return p3, p4, p5, p6, p7
```



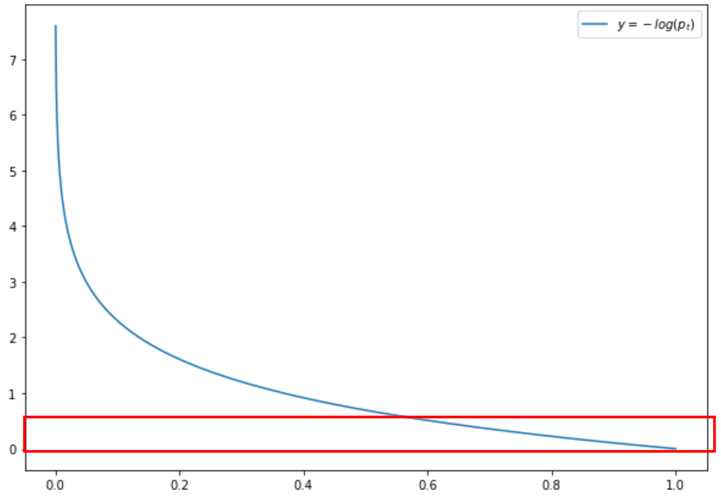
Focal Loss

- Con un numero così alto di anchor point, il numero di box negativi sarà incredibilmente alto
- Perché è un problema?
  - La classification loss sarà dominata dalle componenti negative

$$\mathrm{CE}(p_t, y_t) = y_t \log p_t + (1 - y_t) \log 1 - p_t$$

    - y_t rappresenta la ground truth sul box t

  - Anche con $\mathrm{CE}(p_t, y_t) \gg 0.5$ il contributo è non nullo

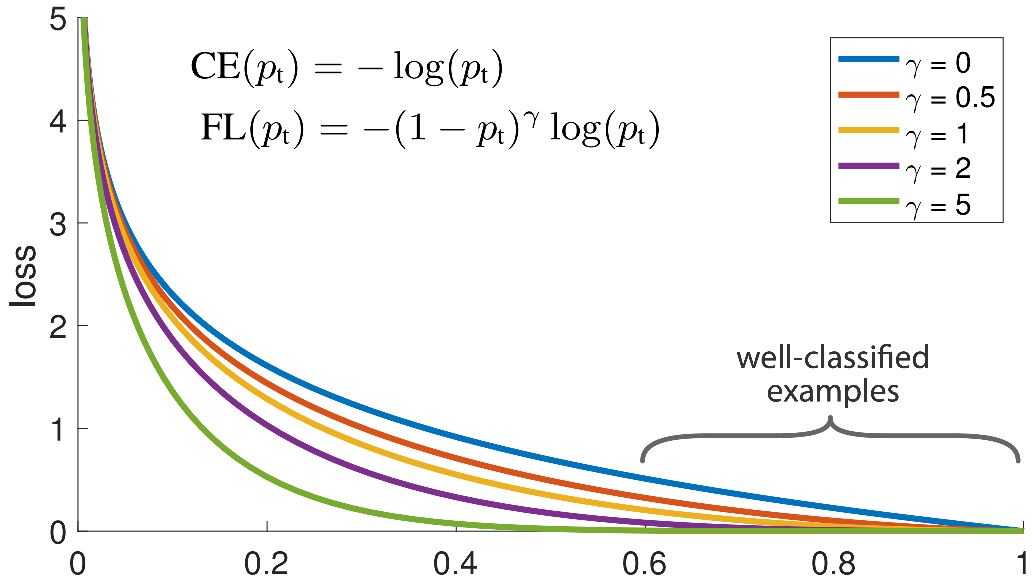


Focal loss

- Focal loss

$$\mathrm{FL}(p_t) = -w_t(1 - p_t)^{\gamma} \log 1 - p_t$$

- Ribilancia il contributo dei true negative
  - Il gradiente è dominata dall'incertezza (sui positivi)



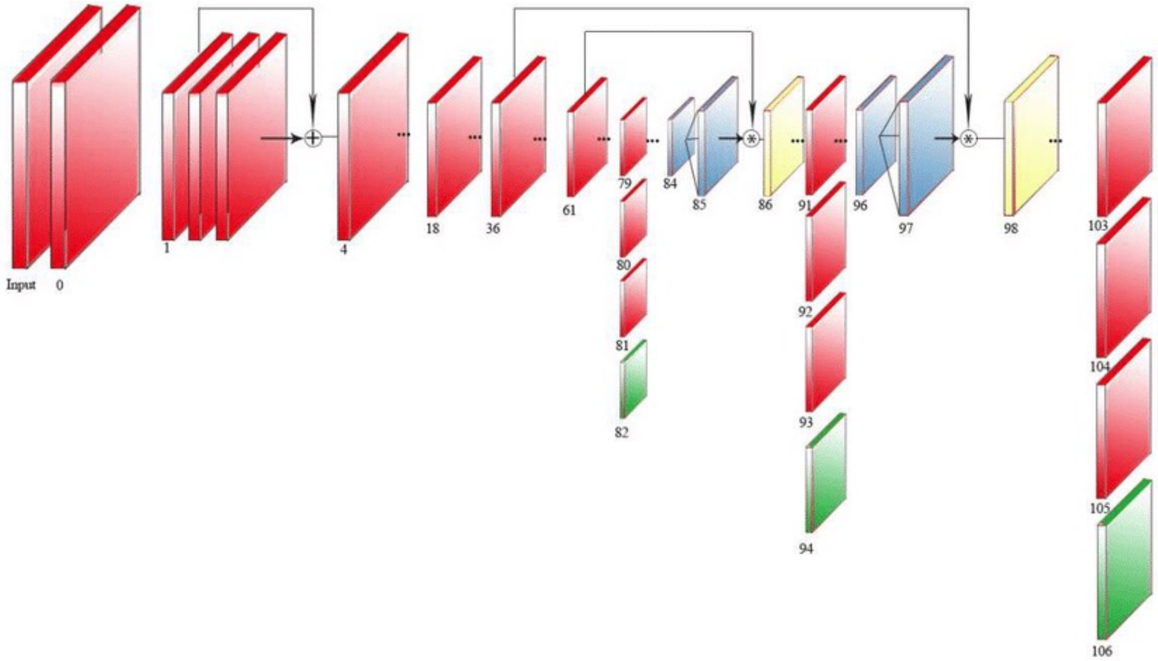
YOLO – You Only Look Once

- Ideato da J. Redmon (https://pjreddie.com/)
- Tre versioni
  - V1, 2016; V2, 2017; - v3, 2018
  - Fast real time object detection
- Idea: limitiamo i bounding boxes utilizzando una griglia prefissata

Split the image into grids — Predict bounding boxes and classifications — Final predictions after non-maximum suppression

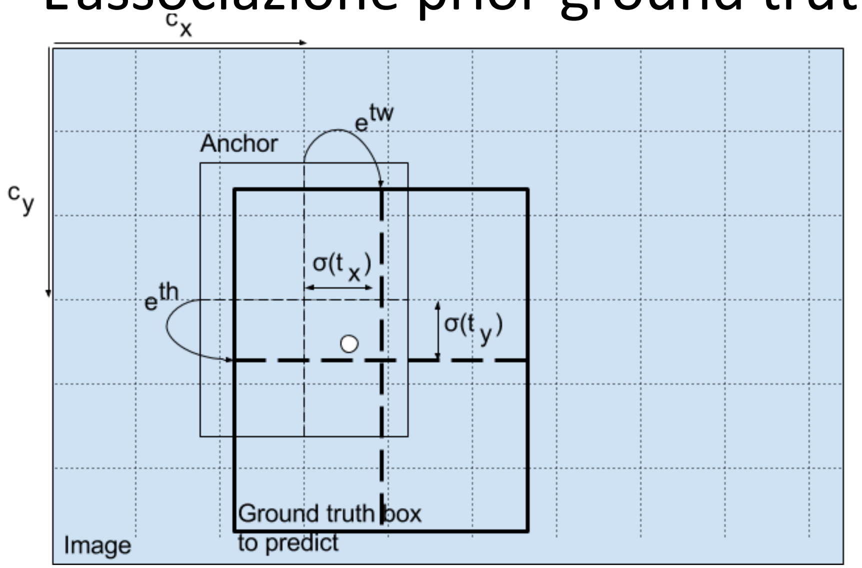
YOLOv3

- Fully Convolutional Networks
  - Simile a SSD
  - 75 convolutional layers
  - skip connections
  - upsampling layers

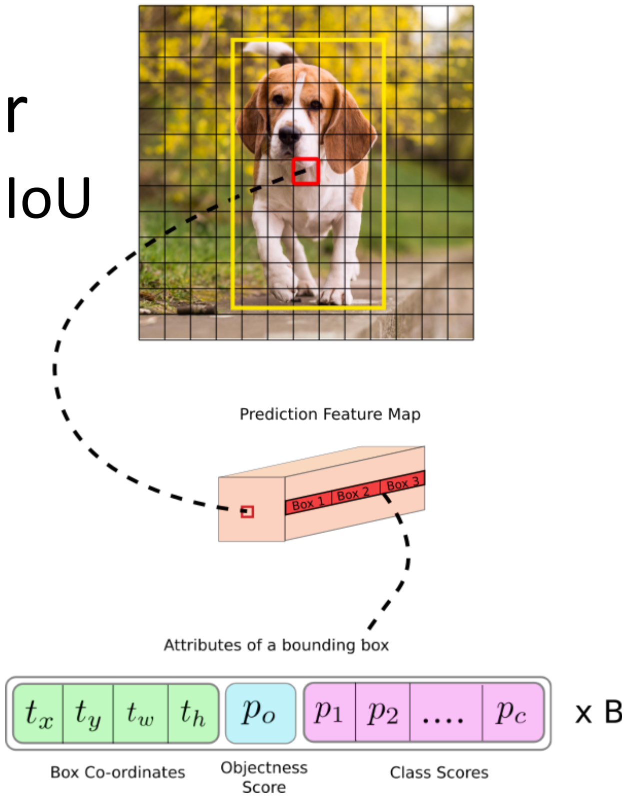


YOLOv3 - Principi

- Ogni cella definisce B Priors
- La cella è responsabile della predizione per l’oggetto il cui centro ricade in essa
- La predizione è effettuata con riferimento alla prior
  - L’associazione prior-ground truth è fatta sulla base dell’IoU

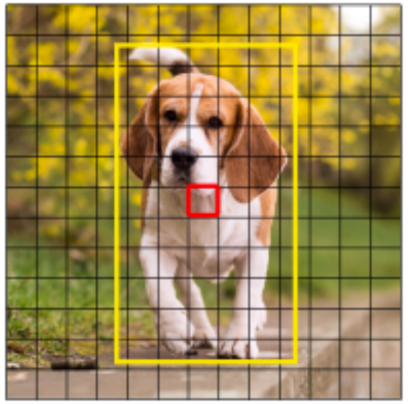
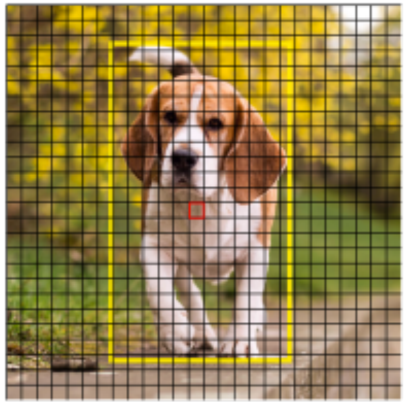
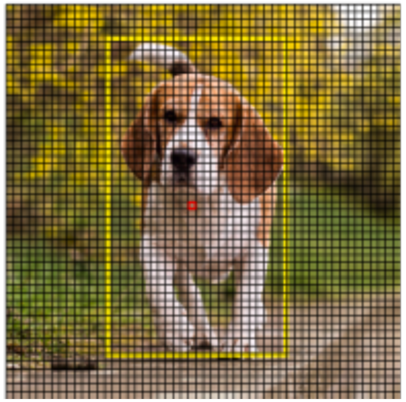


$$b_x = \sigma(t_x) + c_x$$
$$b_y = \sigma(t_y) + c_y$$
$$b_w = p_w e^{t_w}$$
$$b_h = p_h e^{t_h}$$



YOLOv3 - Principi

- Predizione su scale multiple
- Tre griglie con stride 32, 16, 8
  - Su un’immagine 416 x 416, la detection è fatta su griglie 13 x 13, 26 x 26 e 52 x 52

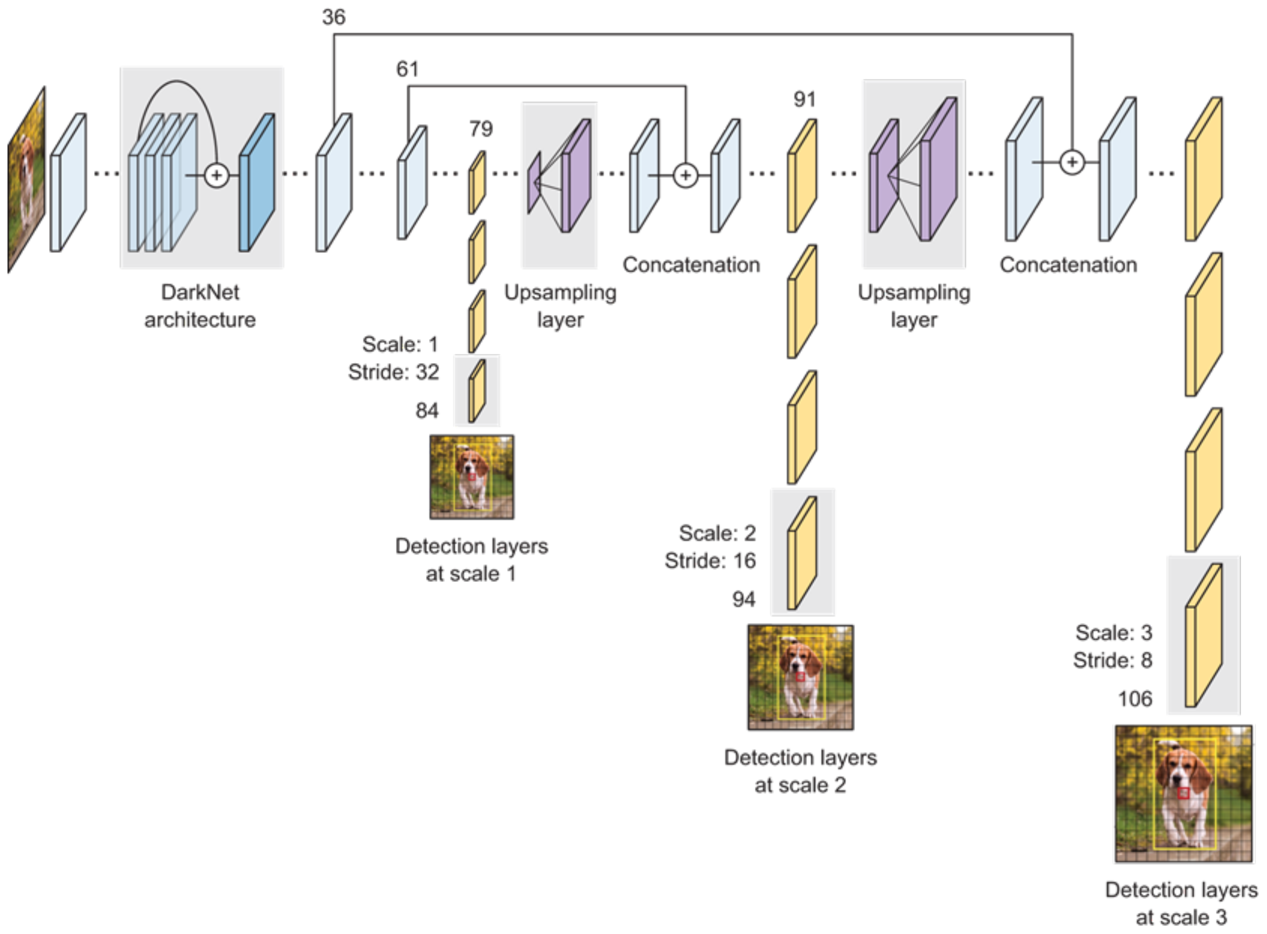
- Risultato: 3549*B predizioni
  - Con B=3, 10647 predizioni

YOLOv3 - Architettura

- 1x1 CONV seguiti da 3x3 CONV
- Residual Blocks
- Feature extractor basato su Darknet-53
    - 106 fully convolutional layers

	Type	Filters	Size	Output
	Convolutional	32	3×3	256×256
	Convolutional	64	$3 \times 3 / 2$	128×128
1×	Convolutional	32	1×1	
	Convolutional	64	3×3	
	Residual			128×128
	Convolutional	128	$3 \times 3 / 2$	64×64
2×	Convolutional	64	1×1	
	Convolutional	128	3×3	
	Residual			64×64
	Convolutional	256	$3 \times 3 / 2$	32×32
8×	Convolutional	128	1×1	
	Convolutional	256	3×3	
	Residual			32×32
	Convolutional	512	$3 \times 3 / 2$	16×16
8×	Convolutional	256	1×1	
	Convolutional	512	3×3	
	Residual			16×16
	Convolutional	1024	$3 \times 3 / 2$	8×8
4×	Convolutional	512	1×1	
	Convolutional	1024	3×3	
	Residual			8×8
	Avgpool		Global	
	Connected		1000	
	Softmax			

YOLOv3 - Architettura



YOLO - Loss

$$
\left.\begin{aligned}
&\lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] \\
&+ \lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]
\end{aligned}\right\} \text{Regression}
$$

$$
\left.\begin{aligned}
&+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2 \\
&+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2
\end{aligned}\right\} \text{Object/no object confidence}
$$

$$
+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \qquad \text{Class prediction}
$$

YOLO - Loss

Cell i contains object, predictor j is responsible for it

$$\lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

$$+ \lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

Small deviations matter less for larger boxes than for smaller boxes

$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$

Confidence for object

$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2$$

Confidence for no object

Down-weight loss from boxes that don't contain objects ($\lambda_{\text{noobj}} = 0.5$)

$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} \left(p_i(c) - \hat{p}_i(c) \right)^2$$

Class probability

YOLOv3 - Loss

$$\lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

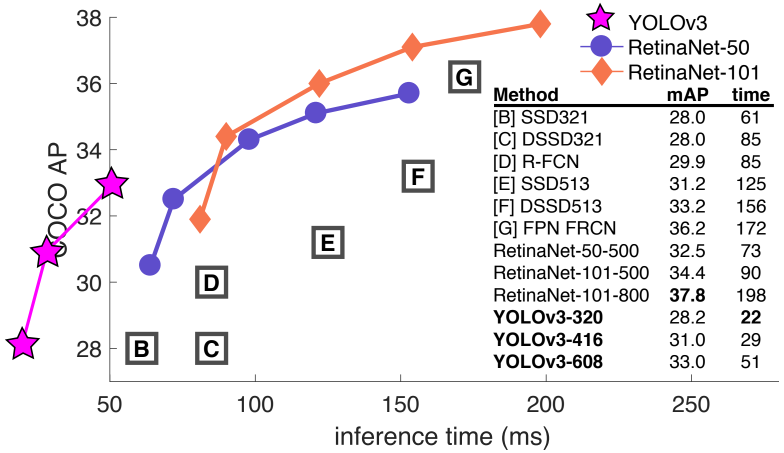
$$+ \lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

$$\boxed{\begin{aligned} &+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2 \\ &+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2 \\ &+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \end{aligned}}$$

Rimpiazzati da
Cross-Entropy/Focal Loss

Sommario

- Estremamente veloce
- Accuratezza comparabile



Metodo	FPS	mAP	Priors
Faster R-CNN	5-7	69,9%	~6000
SSD300	46	74.3%	8732
SSD512	19	76,8%	24564
YOLOv3	~100	57,9%	10647