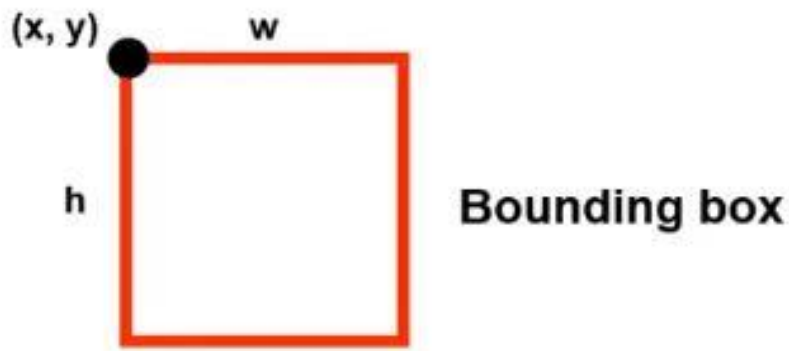
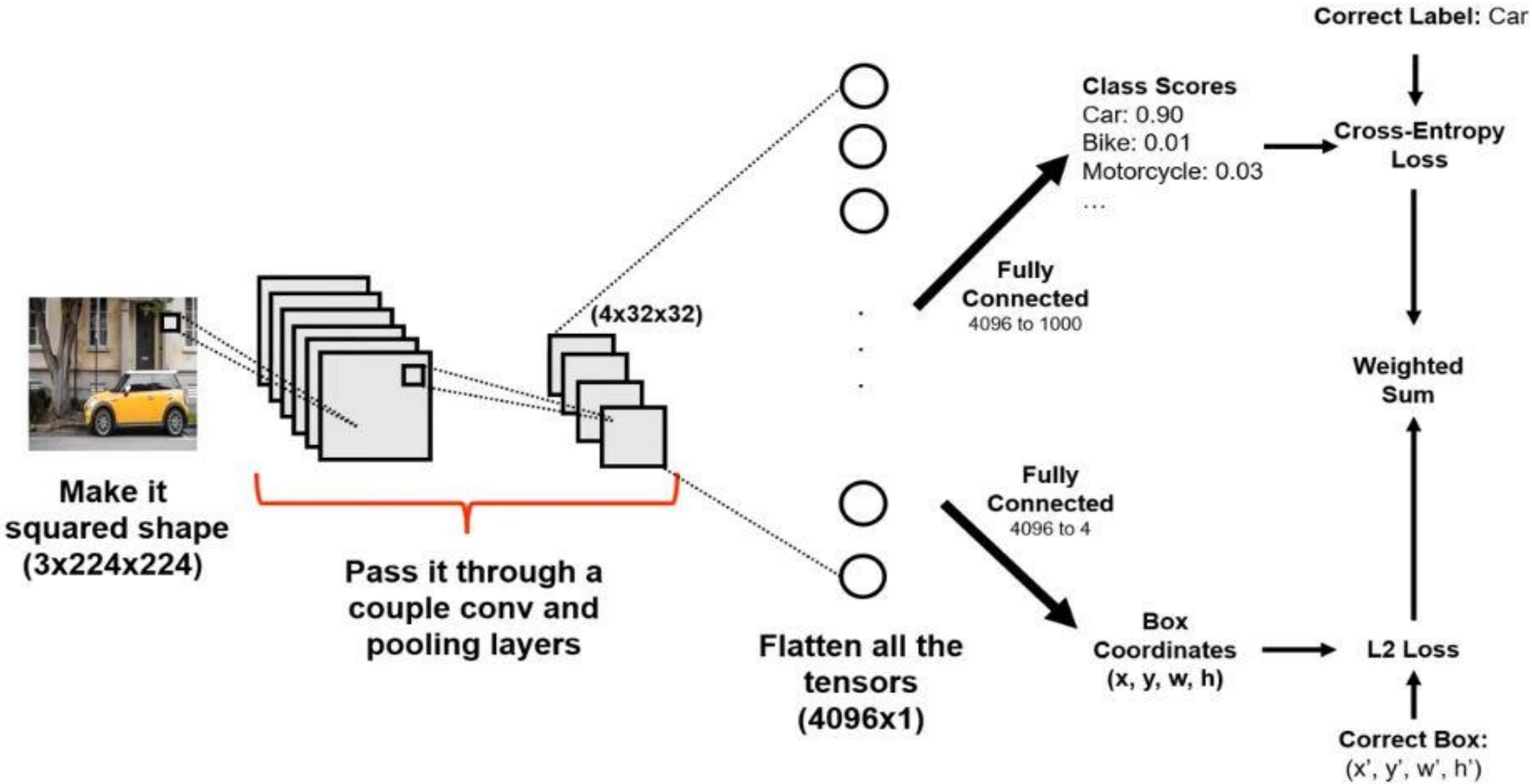

R-CNN

Our Goal

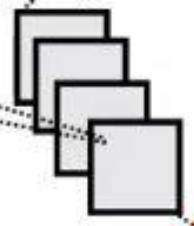


We receive input image


Correct Label: Car
Class Scores
Car: 0.90
Bike: 0.01
Motorcycle: 0.03
...
Cross-Entropy Loss
Fully Connected
4096 to 1000
(4x32x32)
Weighted Sum
Make it squared shape (3x224x224)
Pass it through a couple conv and pooling layers
Flatten all the tensors (4096x1)
Fully Connected
4096 to 4
Box Coordinates (x, y, w, h)
L2 Loss
Correct Box: (x', y', w', h')

Disadvantage: Only one object can be detected :(

Make it squared shape (3x224x224)



(4x32x32)

Pass it through a couple conv and pooling layers

Flatten all the tensors (4096x1)

Fully Connected 4096 to 1000

Class Scores
Car: 0.90
Bike: 0.01
Motorcycle: 0.03
…

Correct Label: Car

Cross-Entropy Loss

Weighted Sum → Loss

Fully Connected 4096 to 4

Box Coordinates (x, y, w, h)

L2 Loss

Correct Box: (x', y', w', h')

Earliest Approach

Earliest Approach

Sliding Window

Earliest Approach

Classify this region!

Neural Network classifier

c + 1 outputs

Car
Motorcycle
Bike
…

Background

Earliest Approach

Classify this region!

Neural Network classifier

Mountain

Earliest Approach

Classify this region!

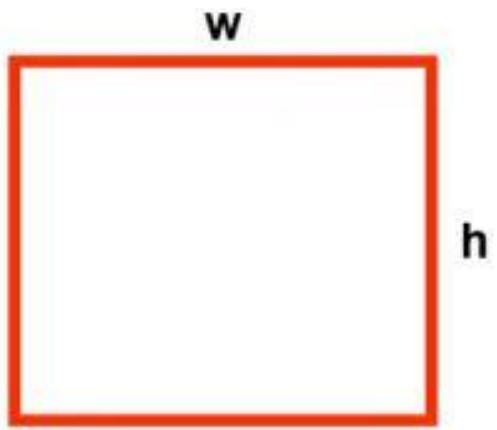
Neural Network classifier

Car

Earliest Approach

W

H



Possible Positions:

(W – w + 1) * (H – h + 1)

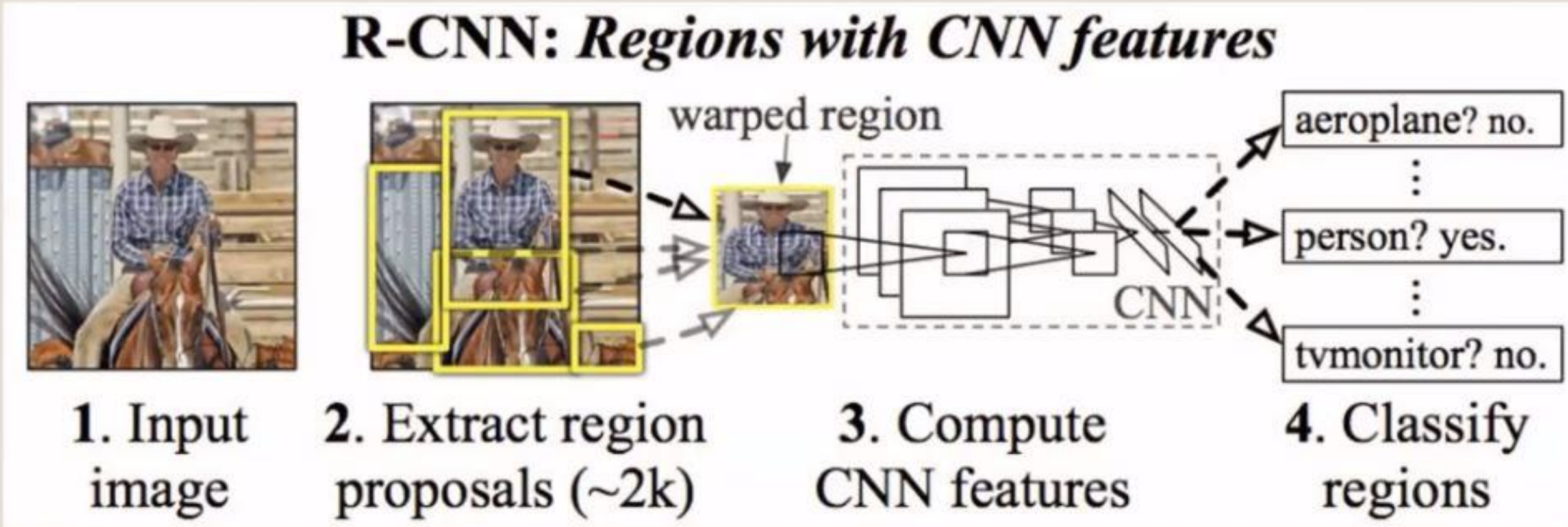
CNN as feature extractor

- What could be the problems?
  - Suppose we have a 600 x 600 image, if sliding window size is 20 x 20, then have (600-20+1) x (600-20+1) = ~330,000 windows
  - Sometimes we want to have more accurate results -> multi-scale detection
    - Resize image
    - Multi-scale sliding window

Disadvantages

- Very Slow
- Number of Picked windows is very huge
- For CNN classifier, needs to apply convolution to each window content
- Same object will be detected in multiple windows (with different Bounding Boxes)

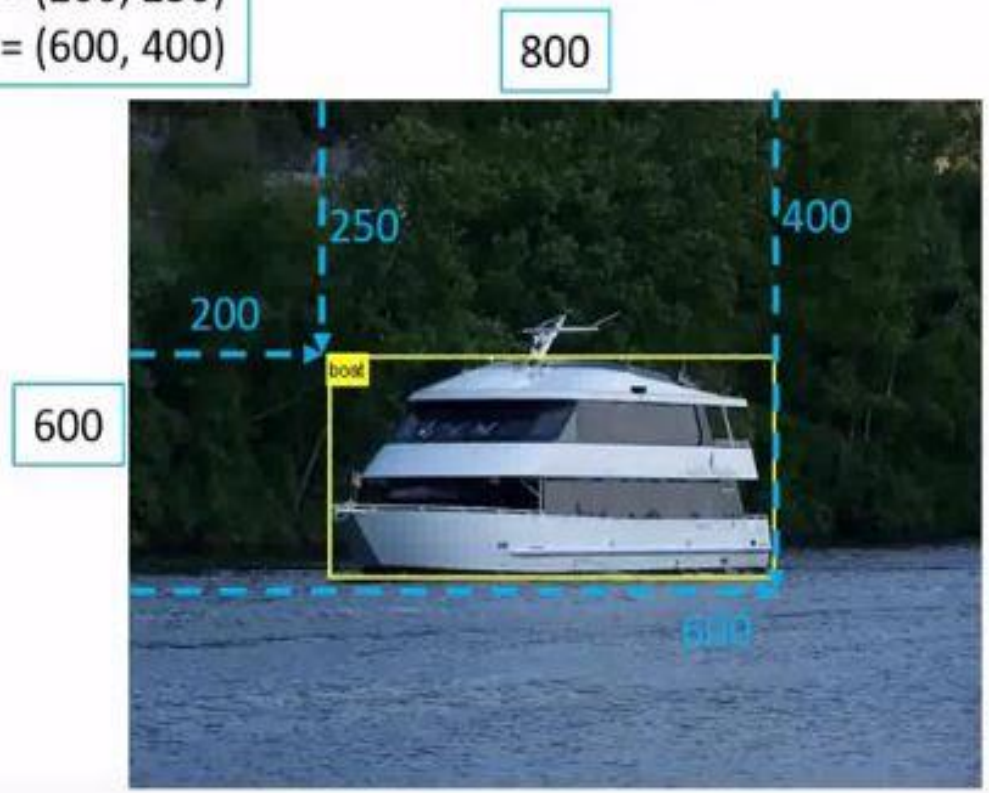
R-CNN

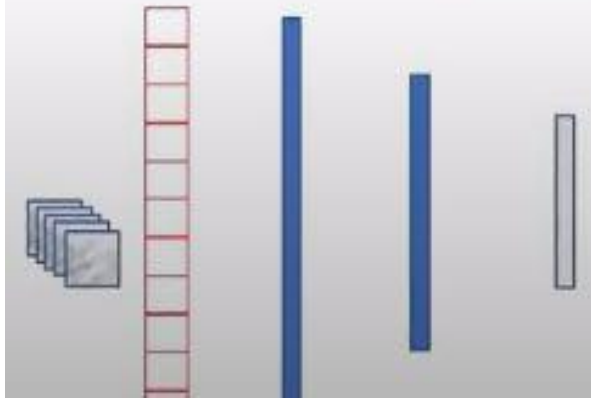


(Girshick, et al., 2014)

Bounding Box Regression Training

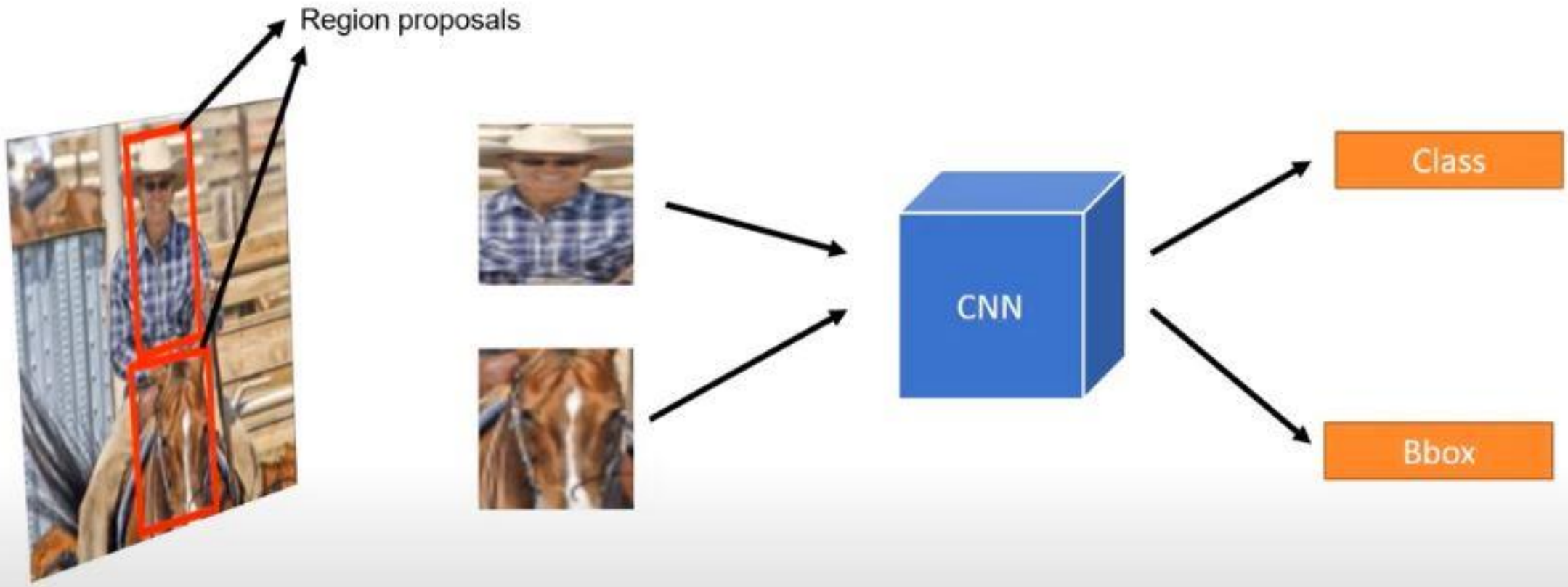
(x1,y1) = (200, 250)
(x2,y2) = (600, 400)





	x1	y1	x2	y2	L2 Loss				
Expected	200	250	600	400					
Prediction	0	0	800	600	$(200-0)^2$	$(250-0)^2$	$(600-800)^2$	$(400-600)^2$	182500
	100	150	700	450	$(200-100)^2$	$(250-150)^2$	$(600-700)^2$	$(400-450)^2$	32500
	210	245	590	405	$(200-210)^2$	$(250-245)^2$	$(600-590)^2$	$(400-405)^2$	250
	200	250	600	400	$(200-200)^2$	$(250-250)^2$	$(600-600)^2$	$(400-400)^2$	0

R-CNN



R-CNN

Region proposal: (p_x, p_y, p_h, p_w)

Bbox

Transform: (t_x, t_y, t_h, t_w)

Output: (b_x, b_y, b_h, b_w)

Translation:

$b_x = p_x + p_w t_w$ (Horizontal translation)

$b_y = p_y + p_h t_h$ (Vertical translation)

Log-space scale transform:

$b_w = p_w \exp(t_w)$ (Horizontal scale)

$b_h = p_h \exp(t_h)$ (Vertical scale)

Region Based CNN

R-CNN (Region proposal + CNN)

Selective Search

Color

Texture

Circles and Curves

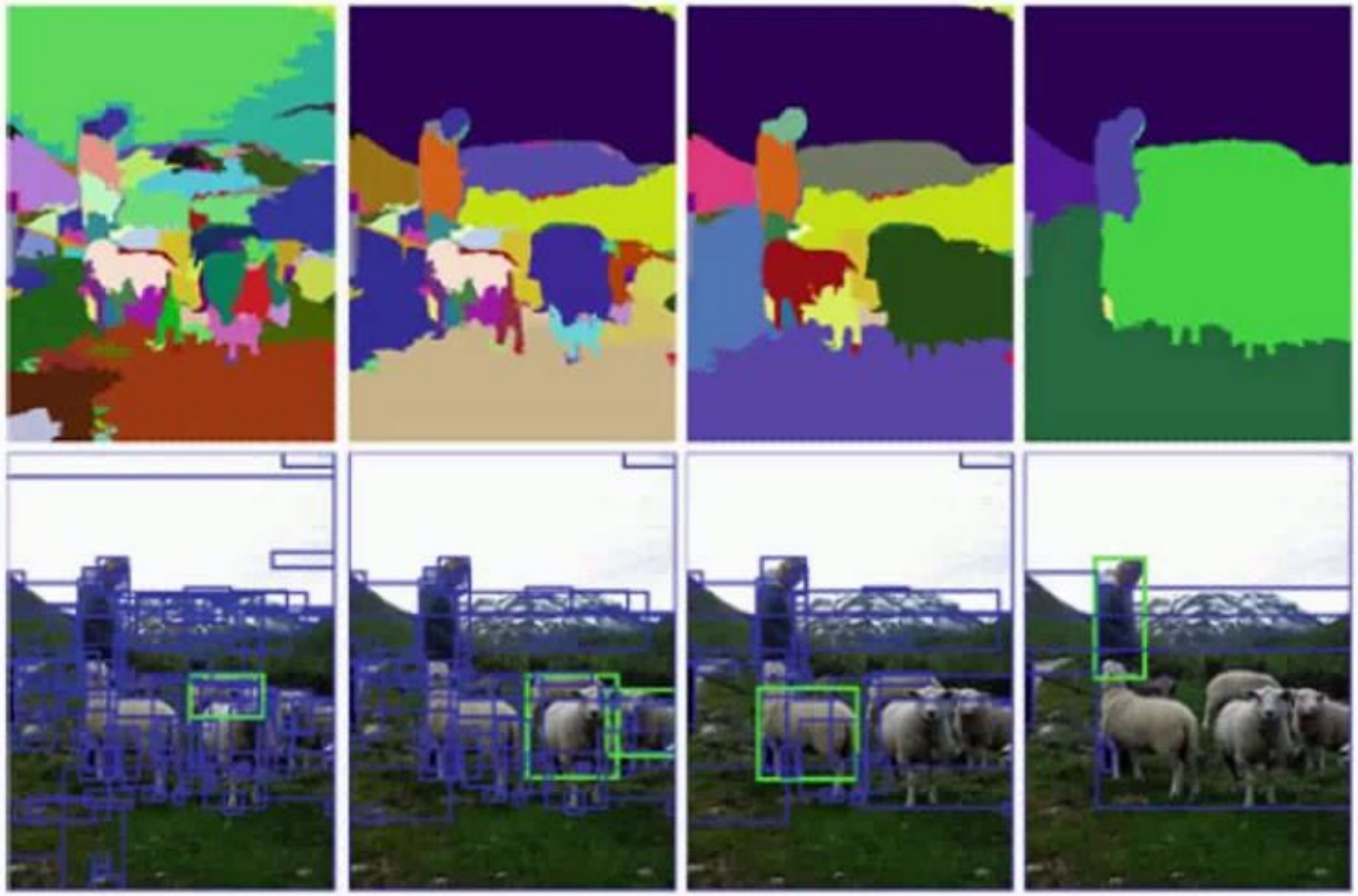
Selective Search (simplified)

- Group based on intensity of the pixels.

(Chandel, 2017)

- We cannot directly use the segmented image as region proposals!
- Group adjacent segments by similarity.

Region Proposal Techniques

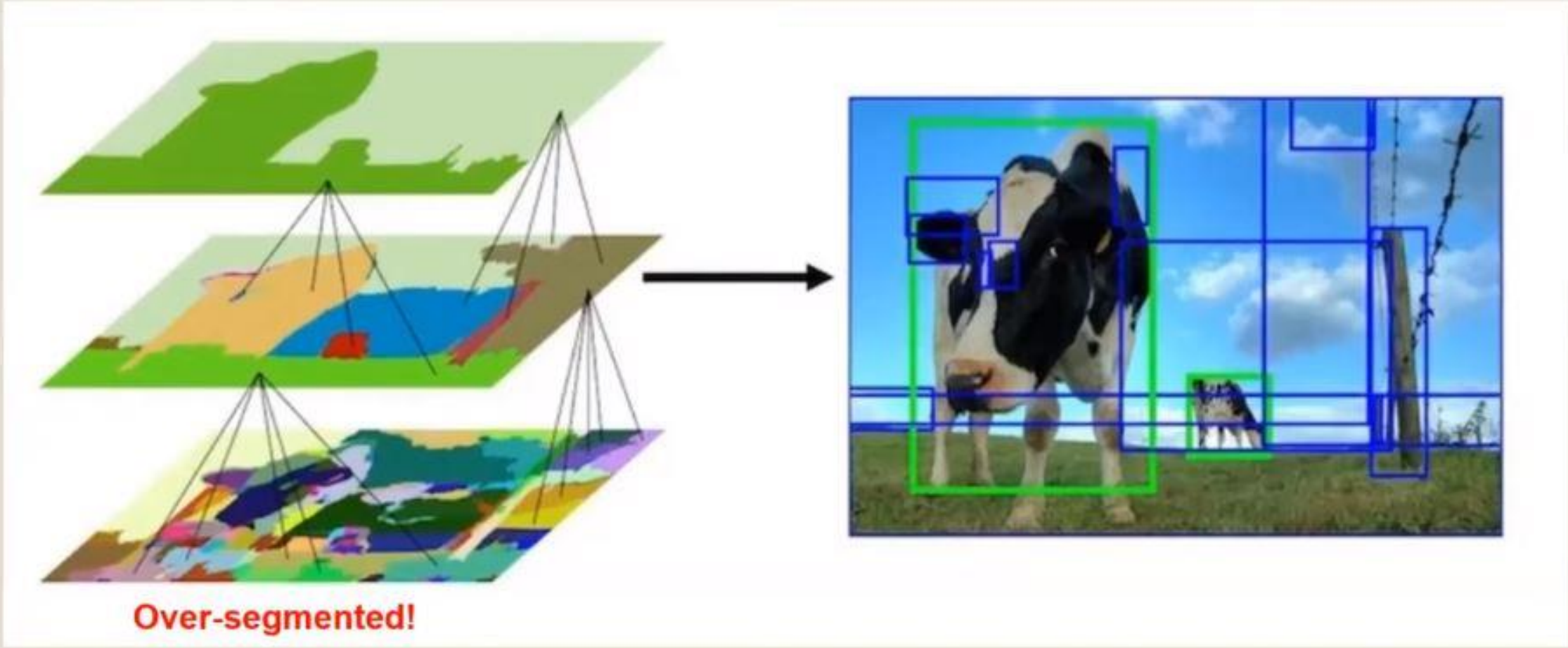


Superpixels Straddling

0	1	4	5	6	0	235	255
1	2	3	3	0	0	240	255
1	2	3	4	0	0	255	255
3	3	4	67	130	120	245	255
5	4	50	120	115	226	250	255
56	45	60	115	120	223	255	255
57	48	58	110	111	215	255	255
59	150	125	255	225	220	255	255

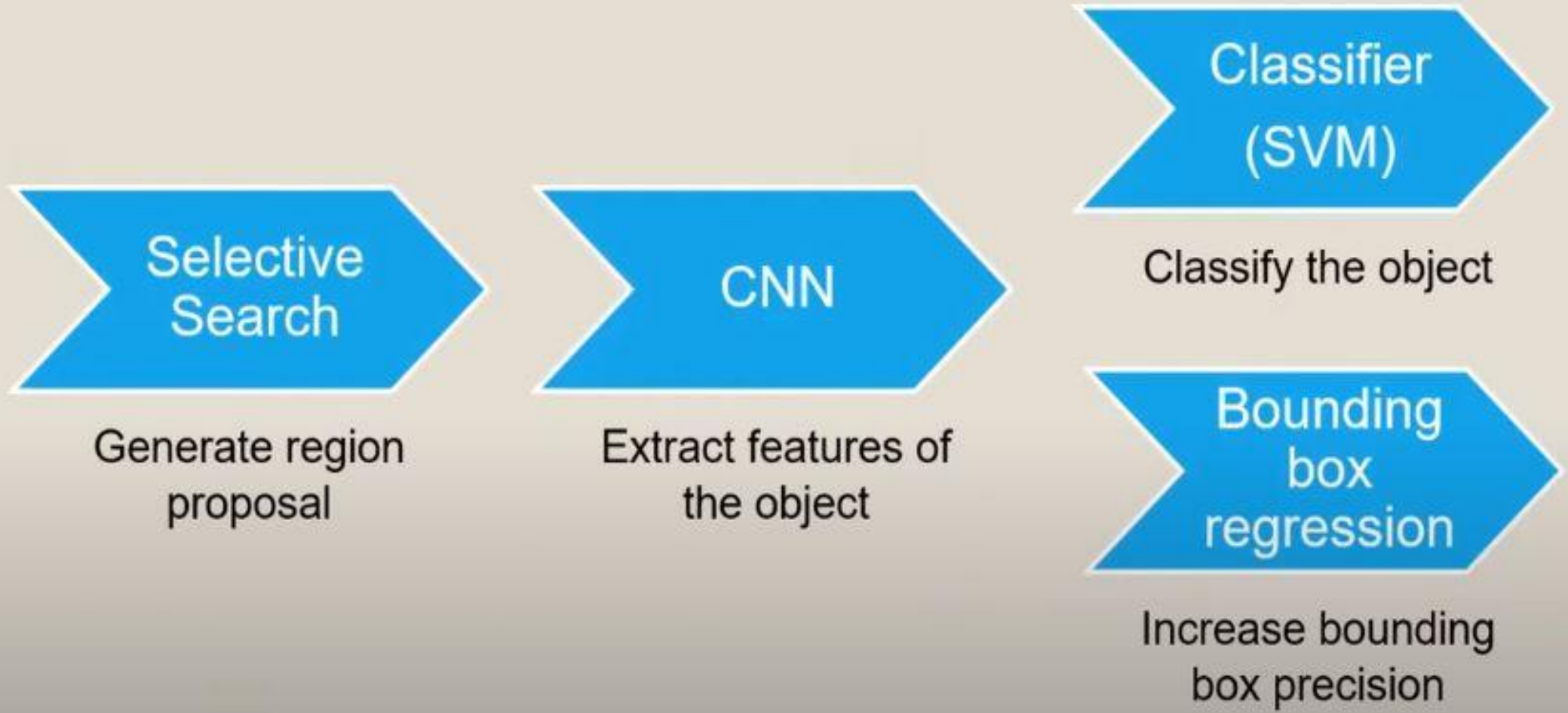
Selective Search for Object Recognition J. R. R. Uijlings, K. E. A. van de Sande, T. Gevers, A. W. M. Smeulders

Selective Search (simplified)



(Chandel, 2017)

R-CNN in a Nutshell...



Disadvantages

- Very Slow
- Cropping of proposed regions
- Requires to apply convolution on each proposed image
- Same object will be detected in multiple windows (with different Bounding Boxes) due to NOT-Optimized Proposed regions

Solution

- Save time by doing CNN one time only on the whole input image

Fast R-CNN

Fast R-CNN

Ross Girshick
Microsoft Research
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Abstract

This paper proposes a Fast Region-based Convolutional Network method (Fast R-CNN) for object detection. Fast R-CNN builds on previous work to efficiently classify object proposals using deep convolutional networks. Compared to previous work, Fast R-CNN employs several innovations to improve training and testing speed while also increasing detection accuracy. Fast R-CNN trains the very deep VGG16 network 9× faster than R-CNN, is 213× faster at test-time, and achieves a higher mAP on PASCAL VOC 2012. Compared to SPPnet, Fast R-CNN trains VGG16 3× faster, tests 10× faster, and is more accurate. Fast R-CNN is implemented in Python and C++ (using Caffe) and is available under the open-source MIT License at https://github.com/rbgirshick/fast-rcnn.

1. Introduction

Recently, deep ConvNets [14, 16] have significantly improved image classification [14] and object detection [9, 19] accuracy. Compared to image classification, object detection is a more challenging task that requires more complex methods to solve. Due to this complexity, current approaches (*e.g.*, [9, 11, 19, 25]) train models in multi-stage pipelines that are slow and inelegant.

Complexity arises because detection requires the accurate localization of objects, creating two primary challenges. First, numerous candidate object locations (often called "proposals") must be processed. Second, these candidates provide only rough localization that must be refined to achieve precise localization. Solutions to these problems often compromise speed, accuracy, or simplicity.

In this paper, we streamline the training process for state-of-the-art ConvNet-based object detectors [9, 11]. We propose a single-stage training algorithm that jointly learns to classify object proposals and refine their spatial locations.

The resulting method can train a very deep detection network (VGG16 [20]) 9× faster than R-CNN [9] and 3× faster than SPPnet [11]. At runtime, the detection network processes images in 0.3s (excluding object proposal time) while achieving top accuracy on PASCAL VOC 2012 [7] with a mAP of 66% (vs. 62% for R-CNN).[1]

1.1. R-CNN and SPPnet

The Region-based Convolutional Network method (R-CNN) [9] achieves excellent object detection accuracy by using a deep ConvNet to classify object proposals. R-CNN, however, has notable drawbacks:

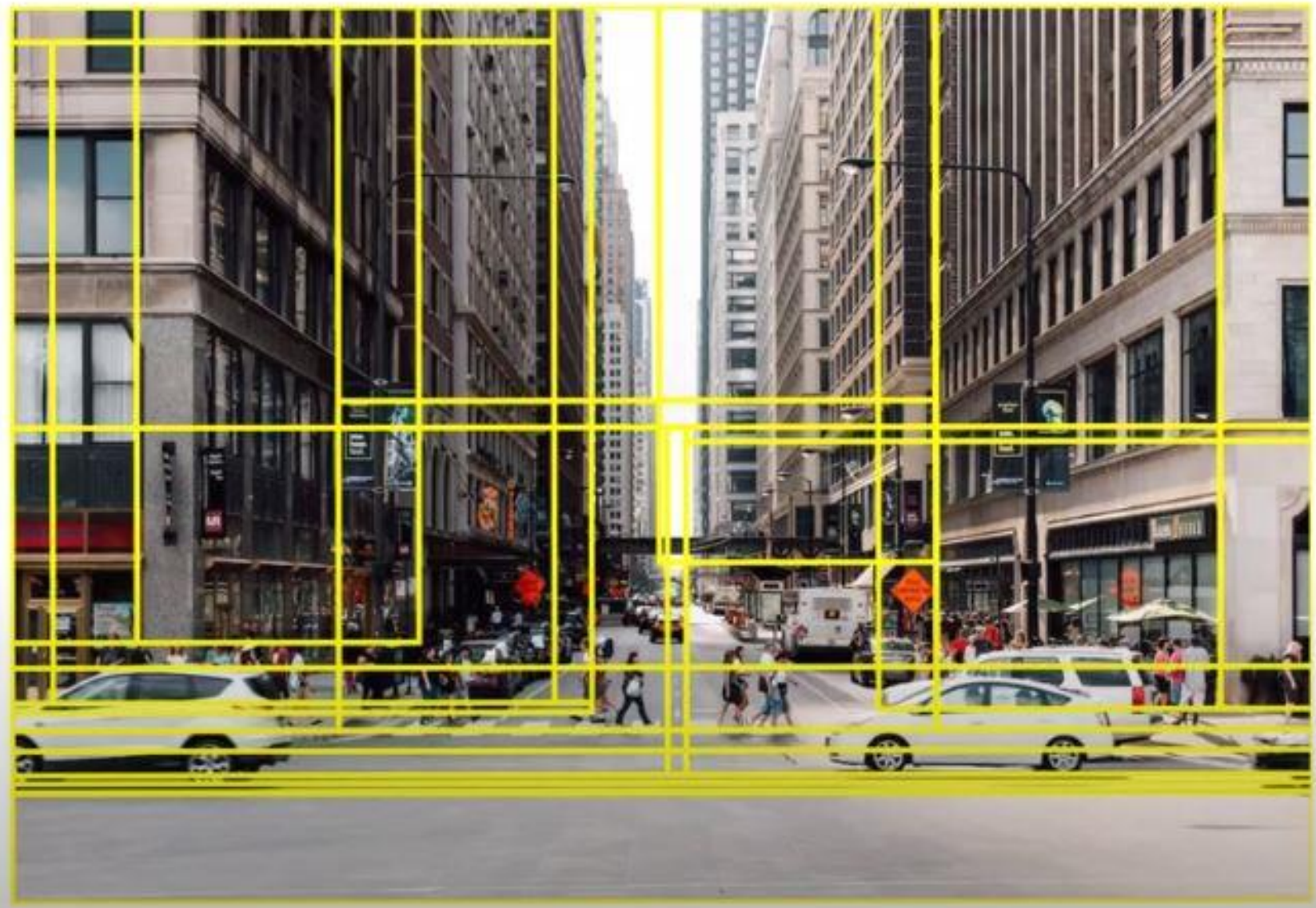
1. **Training is a multi-stage pipeline.** R-CNN first fine-tunes a ConvNet on object proposals using log loss. Then, it fits SVMs to ConvNet features. These SVMs act as object detectors, replacing the softmax classifier learnt by fine-tuning. In the third training stage, bounding-box regressors are learned.
2. **Training is expensive in space and time.** For SVM and bounding-box regressor training, features are extracted from each object proposal in each image and written to disk. With very deep networks, such as VGG16, this process takes 2.5 GPU-days for the 5k images of the VOC07 trainval set. These features require hundreds of gigabytes of storage.
3. **Object detection is slow.** At test-time, features are extracted from each object proposal in each test image. Detection with VGG16 takes 47s / image (on a GPU).

R-CNN is slow because it performs a ConvNet forward pass for each object proposal, without sharing computation. Spatial pyramid pooling networks (SPPnets) [11] were proposed to speed up R-CNN by sharing computation. The SPPnet method computes a convolutional feature map for the entire input image and then classifies each object proposal using a feature vector extracted from the shared feature map. Features are extracted for a proposal by max-pooling the portion of the feature map inside the proposal into a fixed-size output (*e.g.*, 6 × 6). Multiple output sizes are pooled and then concatenated as in spatial pyramid pooling [15]. SPPnet accelerates R-CNN by 10 to 100× at test time. Training time is also reduced by 3× due to faster proposal feature extraction.

[1] All timings use one Nvidia K40 GPU overclocked to 875 MHz.

Last time: R-CNN

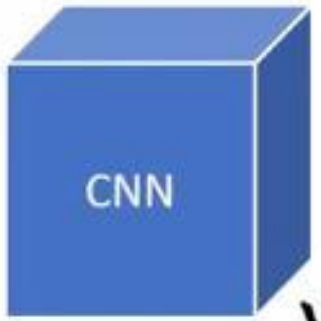
Last time: R-CNN



Last time: R-CNN

2000 region images

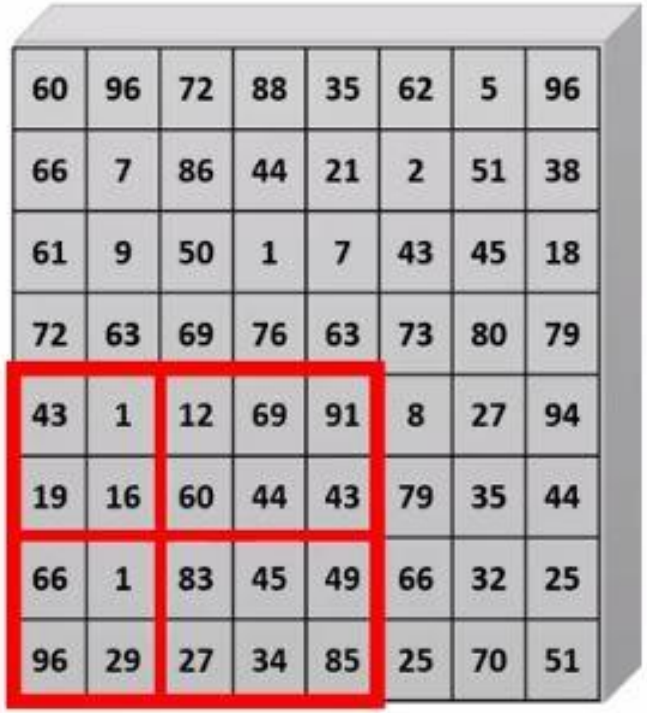
Each of them is 224x224



It is just extracting features

Can't we do this at first and only one time per image?

RoI Pooling

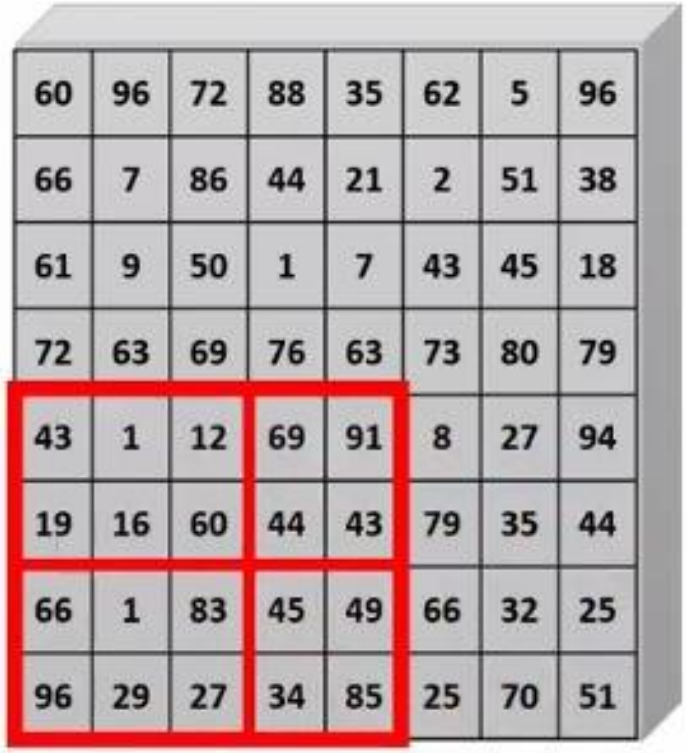


h = 4 w = 5

H = 2 W = 2

RoI max pooling works by dividing the $h \times w$ RoI window into an $H \times W$ grid of sub-windows of approximate size $h/H \times w/W$ and then max-pooling the values in each sub-window into the corresponding output grid cell. Pooling is applied independently to each feature map channel, as in standard max pooling. The RoI layer is simply the special-case of the spatial pyramid pooling layer used in SPPnets [11] in which there is only one pyramid level. We use the pooling sub-window calculation given in [11].

RoI Pooling

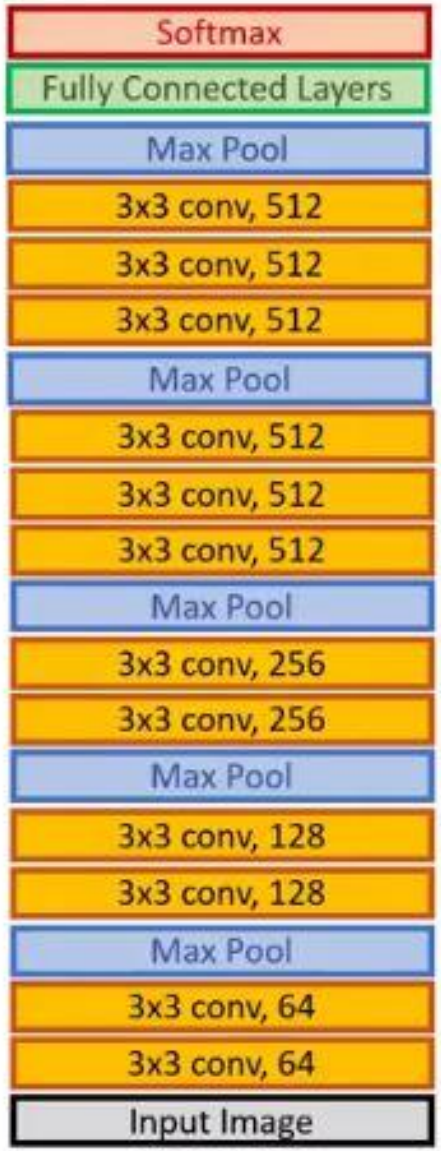


60	91
96	85

RoI max pooling works by dividing the $h \times w$ RoI window into an $H \times W$ grid of sub-windows of approximate size $h/H \times w/W$ and then max-pooling the values in each sub-window into the corresponding output grid cell. Pooling is applied independently to each feature map channel, as in standard max pooling. The RoI layer is simply the special-case of the spatial pyramid pooling layer used in SPPnets [11] in which there is only one pyramid level. We use the pooling sub-window calculation given in [11].

Initializing from pre-trained networks

it undergoes three transformations.



First, the last max pooling layer is replaced by a RoI pooling layer that is configured by setting H and W to be compatible with the net's first fully connected layer (*e.g.*, $H = W = 7$ for VGG16).

Initializing from pre-trained networks

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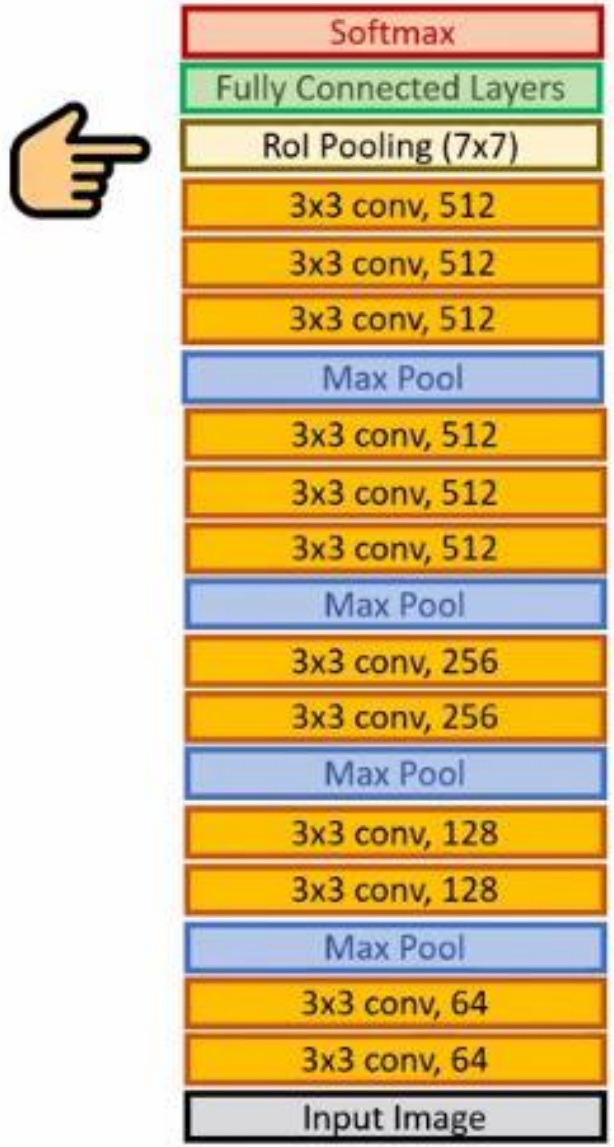

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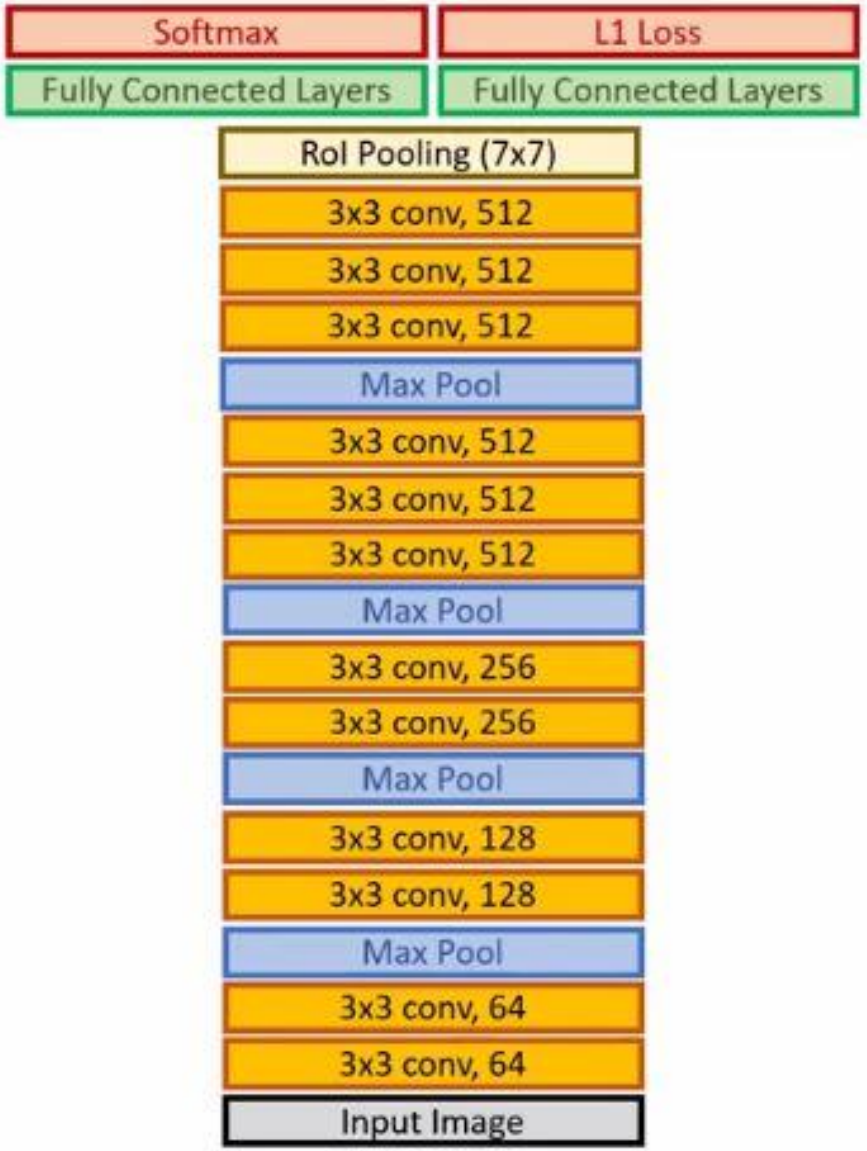

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Second, the network's last fully connected layer and softmax (which were trained for 1000-way ImageNet classification) are replaced with the two sibling layers described earlier (a fully connected layer and softmax over $K + 1$ categories and category-specific bounding-box regressors).

Initializing from pre-trained networks

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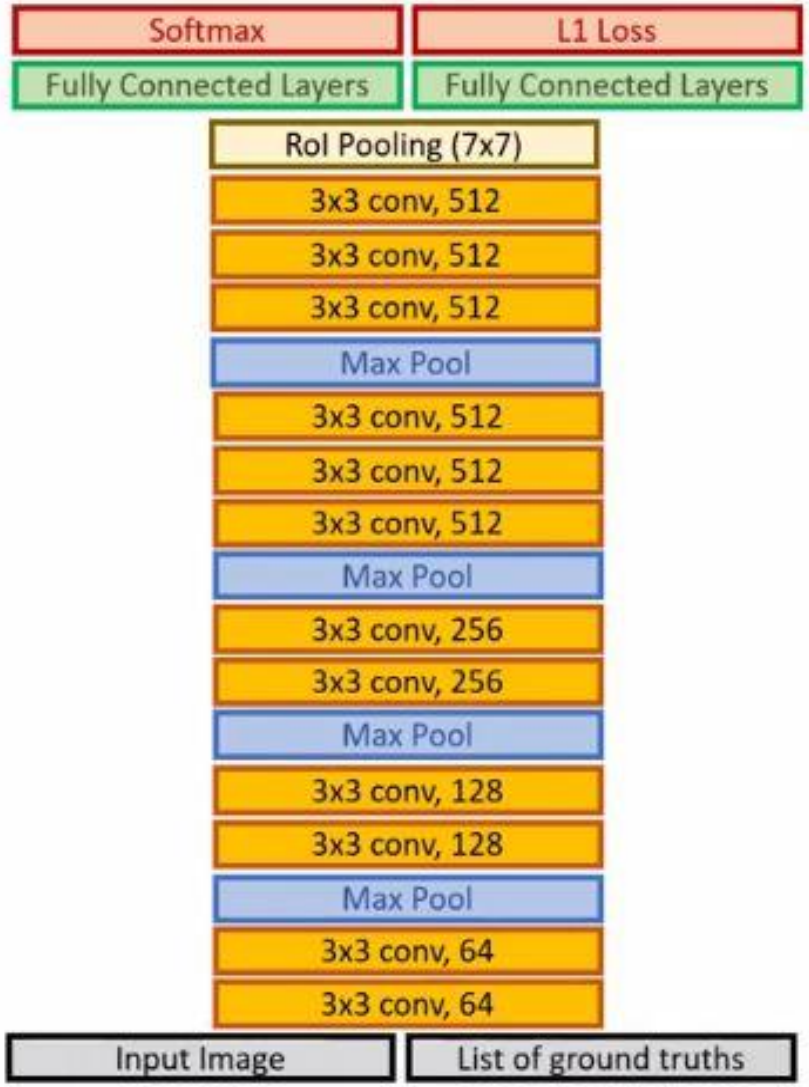

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Third, the network is modified to take two data inputs: a list of images and a list of RoIs in those images.

Fine-tuning for detection

Mini-batch sampling

Mini-batch sampling

Mini-batch 1

Mini-batch 2

Mini-batch 3

Mini-batch 4

Mini-batch sampling

Mini-batch 2


Mini-batch 3


Mini-batch 4


Mini-batch sampling

Mini-batch 2

Mini-batch 3

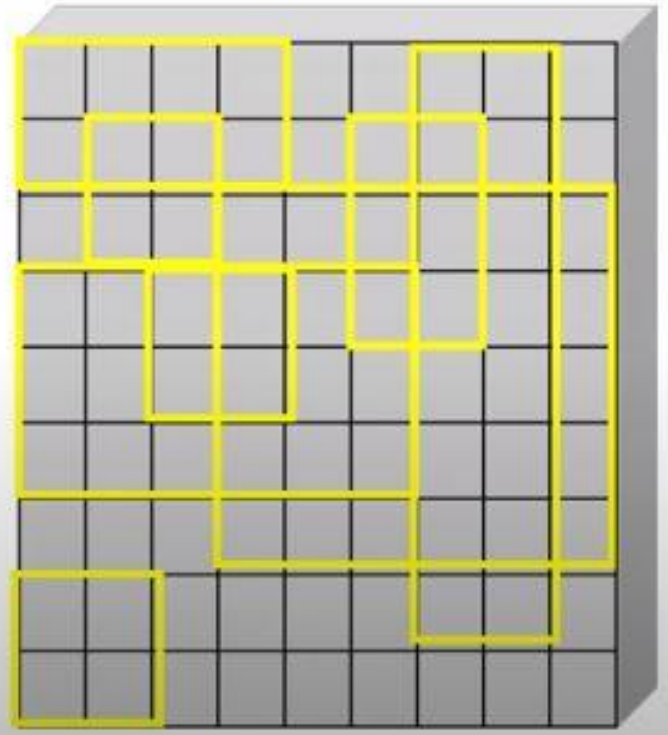
Mini-batch 4

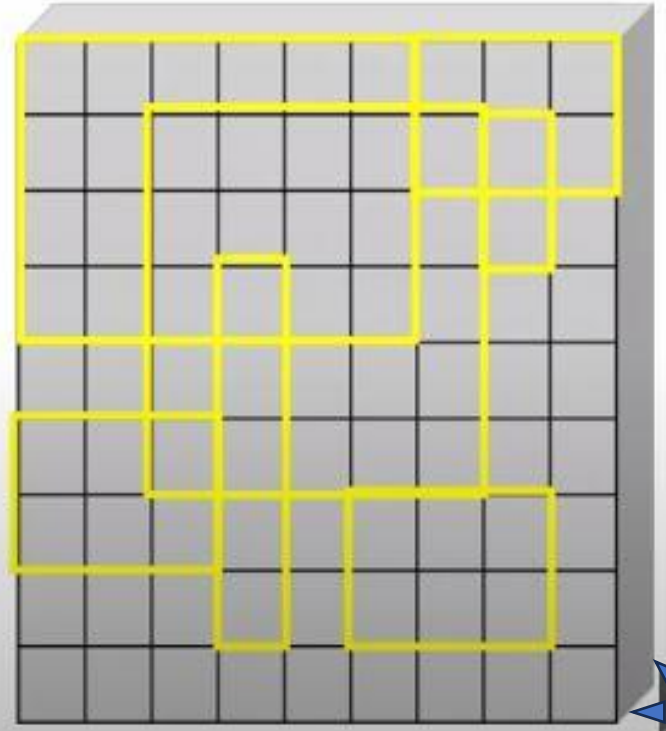
It only selects 64 RoIs from each image!

How???

we take 25% of the RoIs from object proposals that have intersection over union (IoU) overlap with a ground-truth bounding box of at least 0.5.

The remaining RoIs are sampled from object proposals that have a maximum IoU with ground truth in the interval $[0.1, 0.5)$



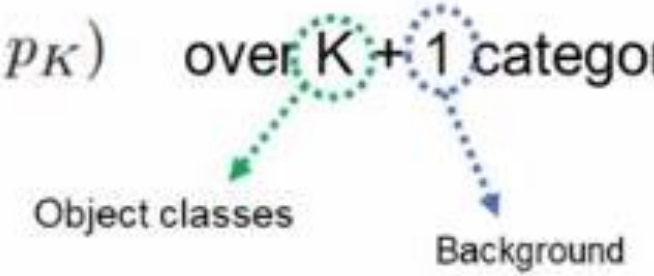


Multi-task Loss

Two sibling output layers:

Ground truths:

1 $p = (p_0, \ldots, p_K)$ over K + 1 categories



u

2 $t^k = (t^k_{\mathrm{x}}, t^k_{\mathrm{y}}, t^k_{\mathrm{w}}, t^k_{\mathrm{h}})$

v

$$L(p, u, t^u, v) = L_{\mathrm{cls}}(p, u) + \lambda[u \geq 1] L_{\mathrm{loc}}(t^u, v),$$

Multi-task Loss

Two sibling output layers:

1 $p = (p_0, \ldots, p_K)$ over K + 1 categories

Object classes — Background

2 $t^k = (t_x^k, t_y^k, t_w^k, t_h^k)$

Ground truths:

u

v

$$L(p, u, t^u, v) = L_{\text{cls}}(p, u) + \lambda[u \geq 1] L_{\text{loc}}(t^u, v),$$

- $L_{\text{cls}}(p, u) = -\log p_u$ $\quad (L_{CE} = -\sum_i p_i^* \log p_i)$

  p_i^*: True class distribution; p_i: Predicted class distribution

- $[u \geq 1]$ evaluates to 1 when $u \geq 1$ and 0 otherwise.

- $L_{\text{loc}}(t^u, v) = \sum_{i \in \{x,y,w,h\}} \text{smooth}_{L_1}(t_i^u - v_i),$

in which

$$\text{smooth}_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise,} \end{cases}$$

Scale Invariance

Scale Invariance

Brute force

Image pyramids

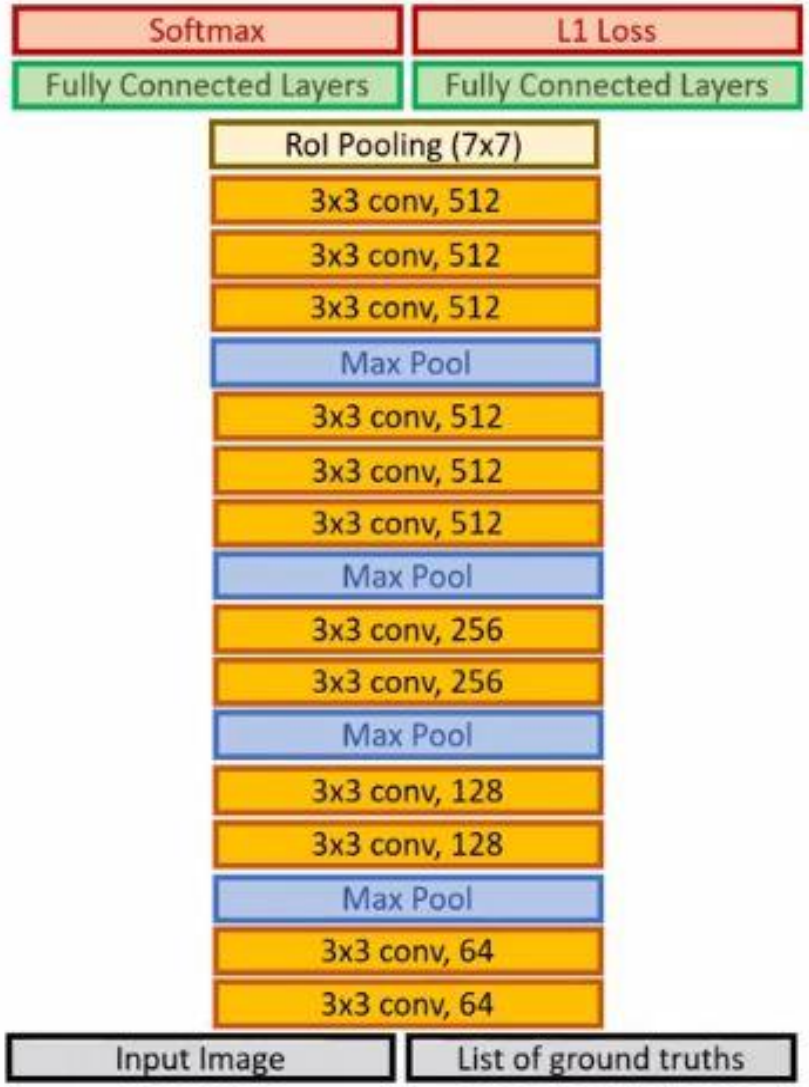
Fast R-CNN

output

- Faster RCNN

Initializing from pre-trained networks

it undergoes three transformations.



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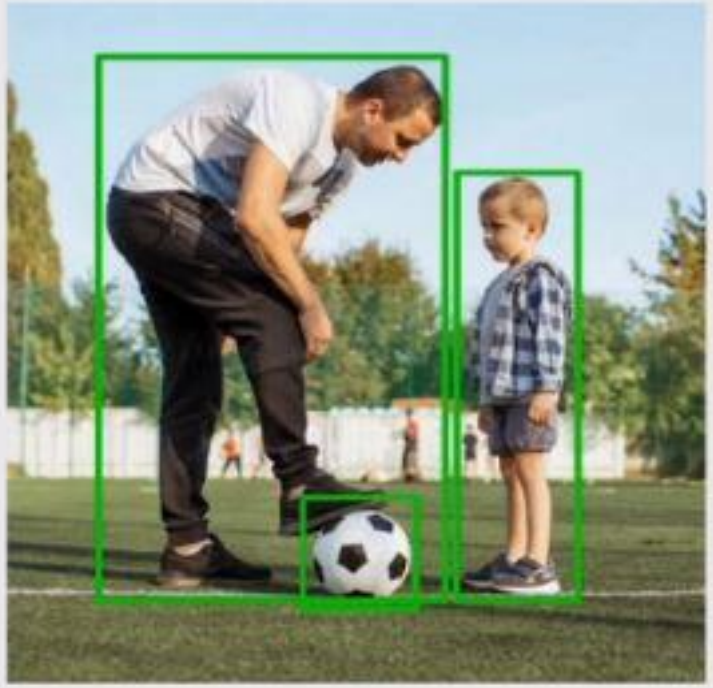
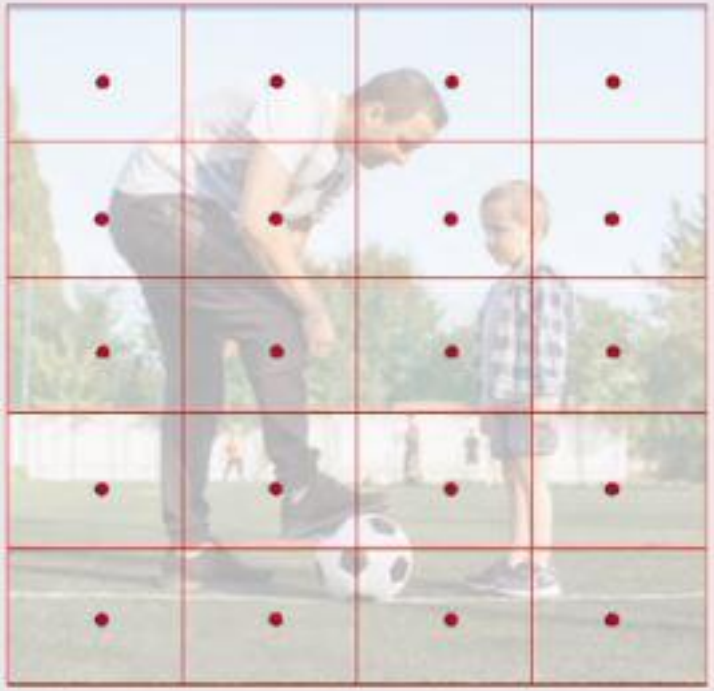
Region Proposal Network

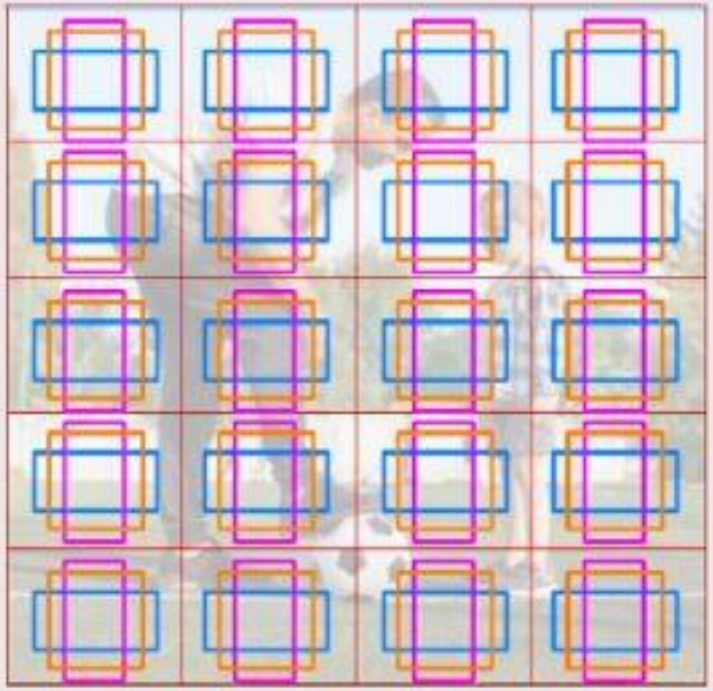
RPN



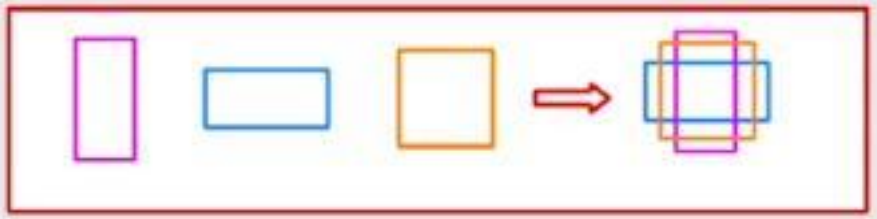
Input Image



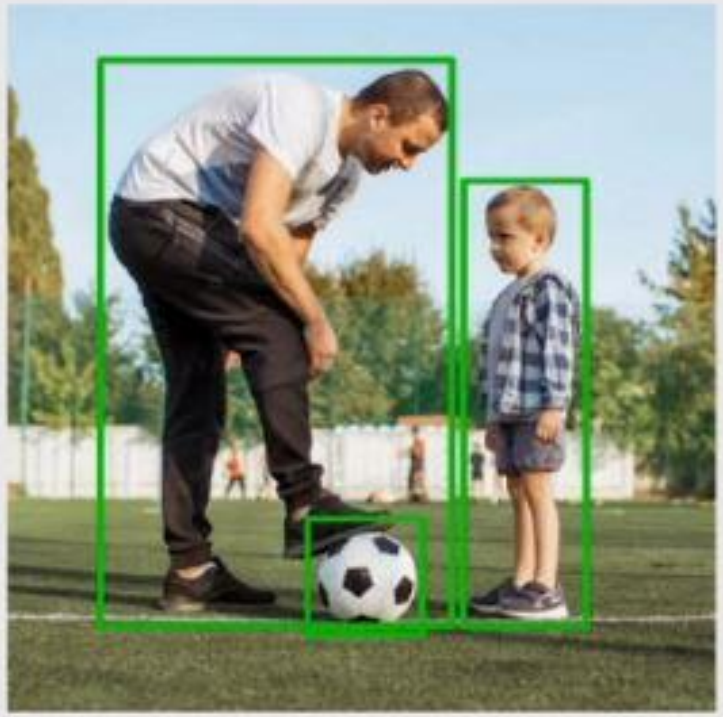
Define Anchor Points



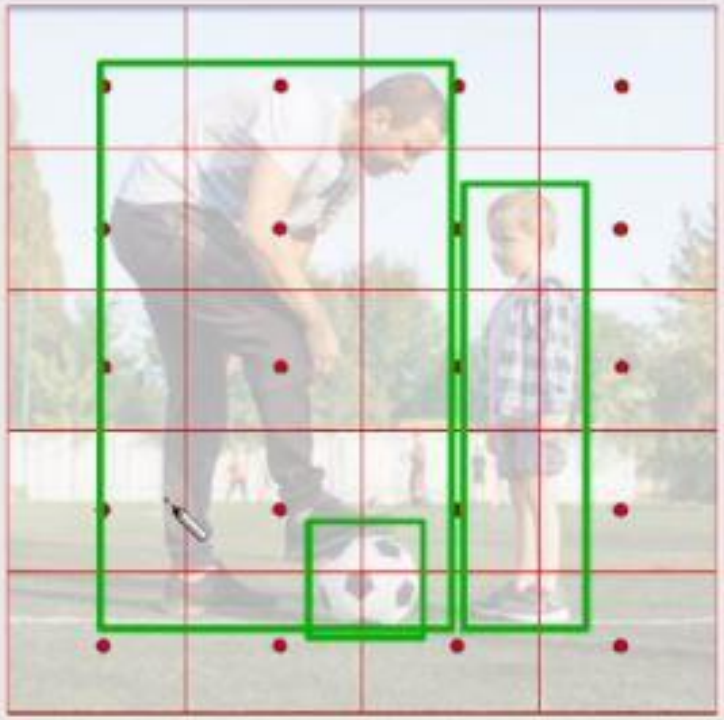
Define Anchor Boxes
(centered at Anchor Points)



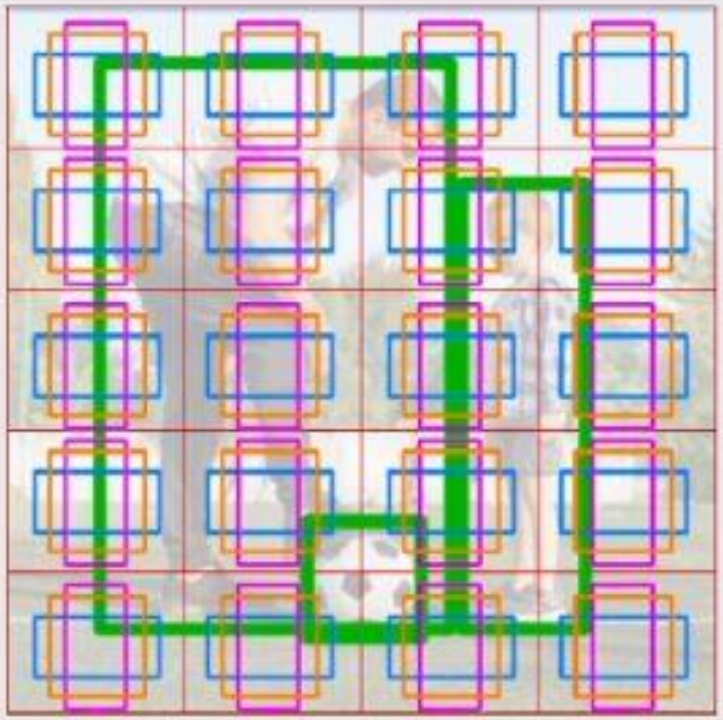
Define Anchor Boxes
Different Scales, Different Aspect ratios
In original paper: 3 scales, 3 ratios
(9 anchor boxes)



Input Image

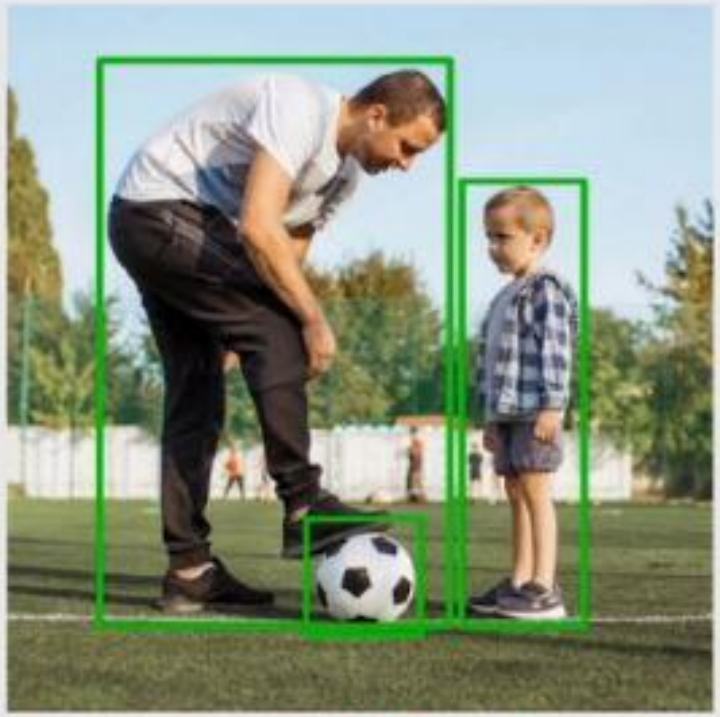


Define Anchor Points

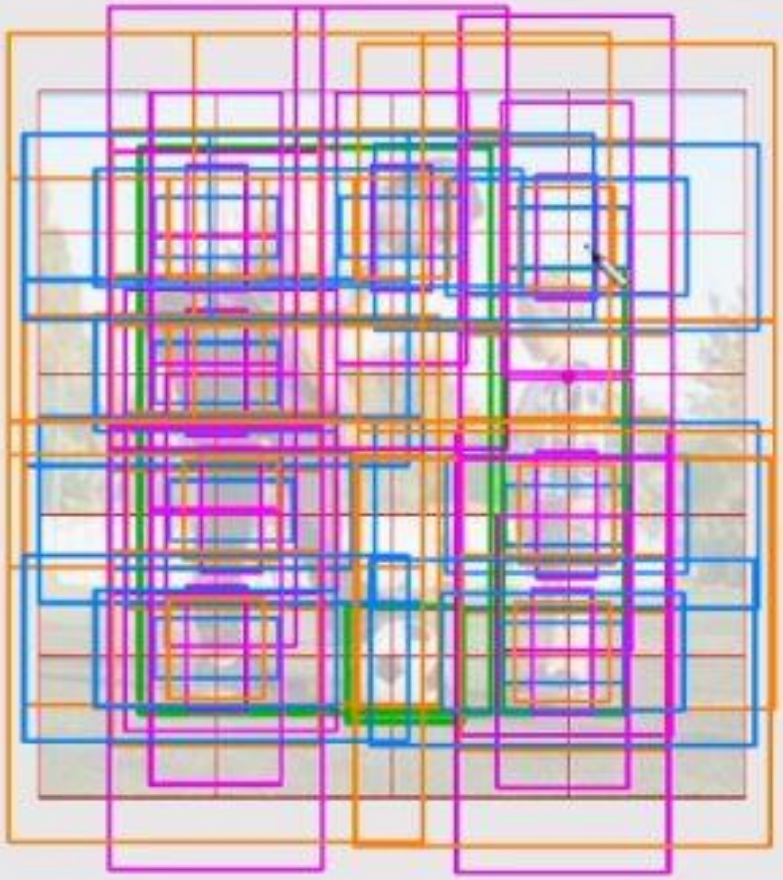


Define Anchor Boxes (centered at Anchor Points)

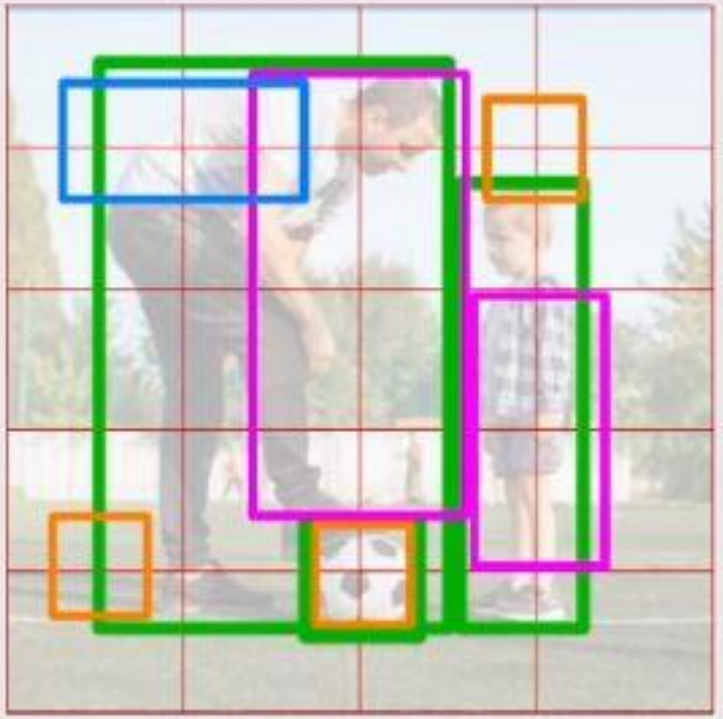
- *Selected sizes of Anchor boxes are too small (with respect to objects)*
- *Only Ball may be detected by anchor boxes*
- *Other anchor boxes will be assumed as background (IOU with ground truth is small)*



Input Image
with Ground Truth

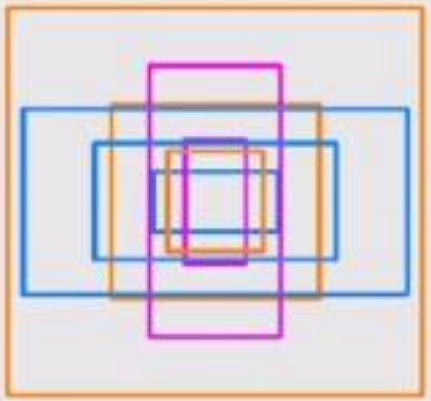


Define Anchor Points



*Example of Some Anchor boxes with High IOU (**Objects**)*

*Others with small IOU (**Background**)*



Define Larger Anchor Boxes
3 scales, 3 ratios (9 anchor boxes)

Note: Many Overlaps between boxes (No Problem)

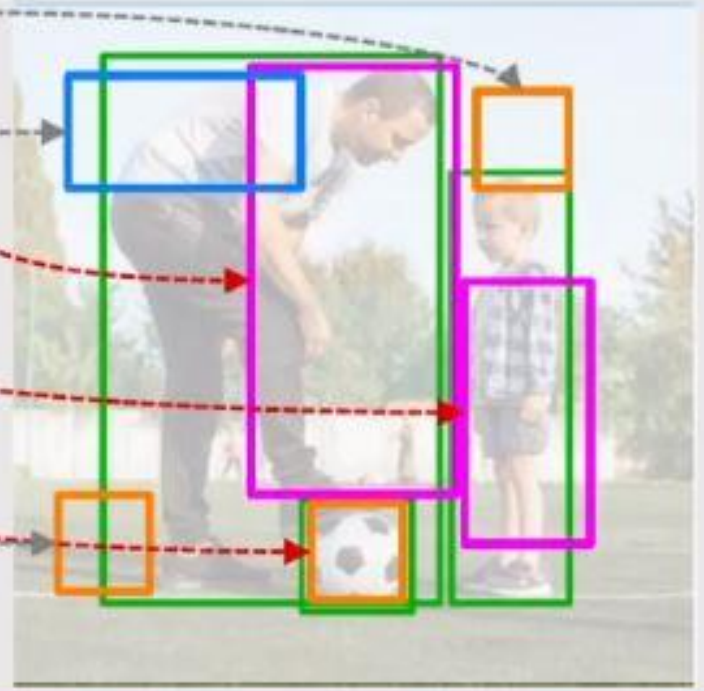
Anchor Boxes classification

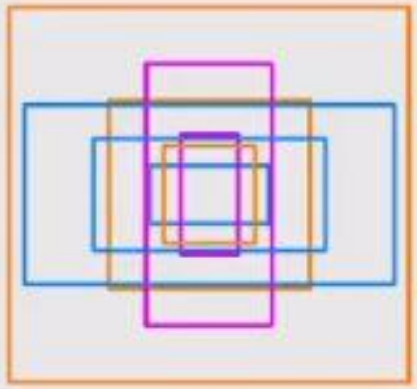
Some Anchor boxes with High IOU
(Objects)

Object

Some Anchor Boxes with small IOU
(Background)

Background





Define Larger Anchor Boxes
3 scales, 3 ratios (9 anchor boxes)

Note: Many Overlaps between boxes
(No Problem)

Number of Anchor Boxes (in the above example):

If K=9 Anchor boxes per anchor point (3 scales * 3 ratios)

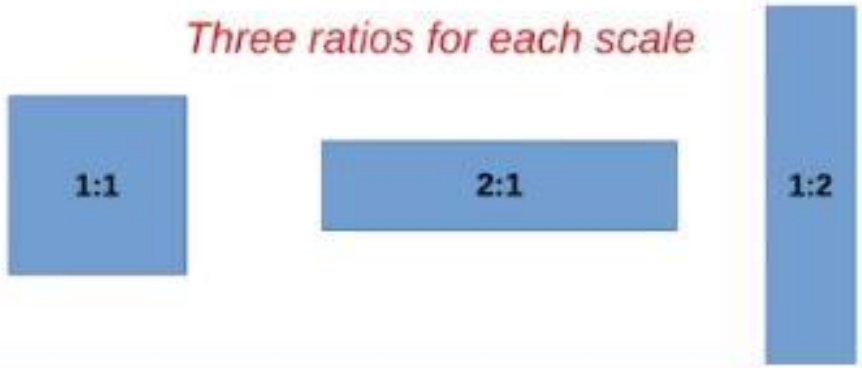
# of anchor points = 3 * 4 = 12

Total Number of Anchor boxes (within Image)=12 * 9=108 boxes

Use Different Scales

For Example: *128 x 128* *256 x 256* *512 x 512*

Three ratios for each scale



[2] Anchor Boxes Parameters

Anchor Boxes Parameters

Each Anchor Box is characterized by two vectors:

[1] Content Classification vector:

- Enclose Object
- Part of the Background
- Mix between part of object and part of background

Classification (or ***Objectness***) Vector Length=2

[2] Bounding Box offsets vector [w.r.t Ground truth box of its enclosed object]

(for Anchor boxes classified as containing objects ONLY)

- Displacement between both centers
- Ratio between Width and height of Anchor Box and Ground Truth Box

Regressor Vector Length = 4

[1] Classification of Anchor Boxes

Assign class label to each anchor as:

- Anchor Box encloses Object (**Positive** Anchor Box)
- Anchor Box encloses Background (**Negative** Anchor Box)
- Anchor Box encloses part of Object and Part of Background (**Mix** Anchor Box)

Remember:

Classification of Anchor Boxes is based on IOU Between Anchor Box and Ground Truth Object Boxes in the image

[1] Classification of Anchor Boxes

Classification of Anchor Boxes is based on IOU Between Anchor Box and Ground Truth Object Boxes in the image

Anchor Box is classified as Positive if:

1- Has the **Highest IOU** with one of he ground truth boxes (one of the objects)

2- Has **IOU ≥ 0.7** with any of the ground truth boxes (even if not the Highest)

Anchor Box is classified as Negative if:

1- Has **IOU ≤ 0.3** with ALL ground truth boxes (all objects)

Anchor Box is classified as Mix (Undetermined) if:

1- Neither Positive Nor Negative

[1] Classification of Anchor Boxes

Positive

Highest IOU with the Father Object $\begin{bmatrix}1\\0\end{bmatrix}$

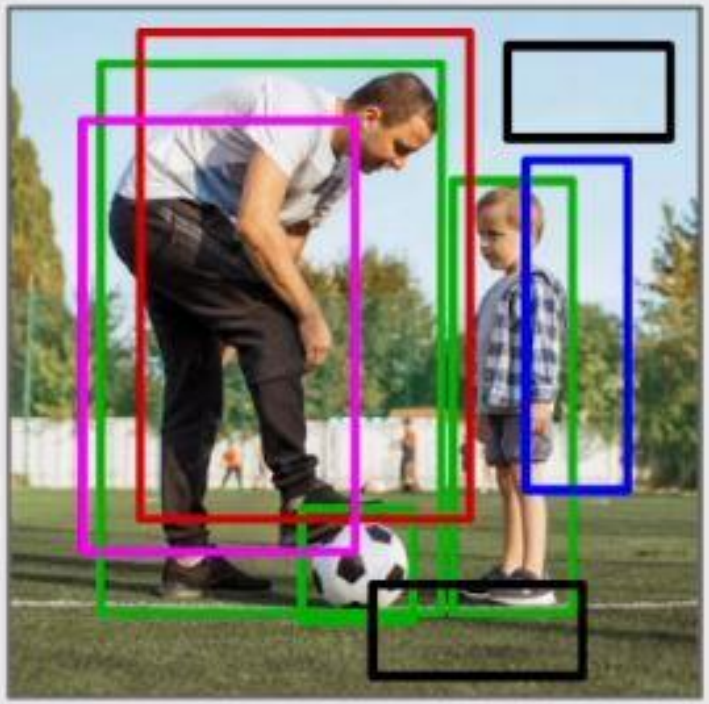
IOU >0.7 with the Father Object (but not the highest)

Negative

IOU <0.3 with ALL Objects $\begin{bmatrix}0\\1\end{bmatrix}$

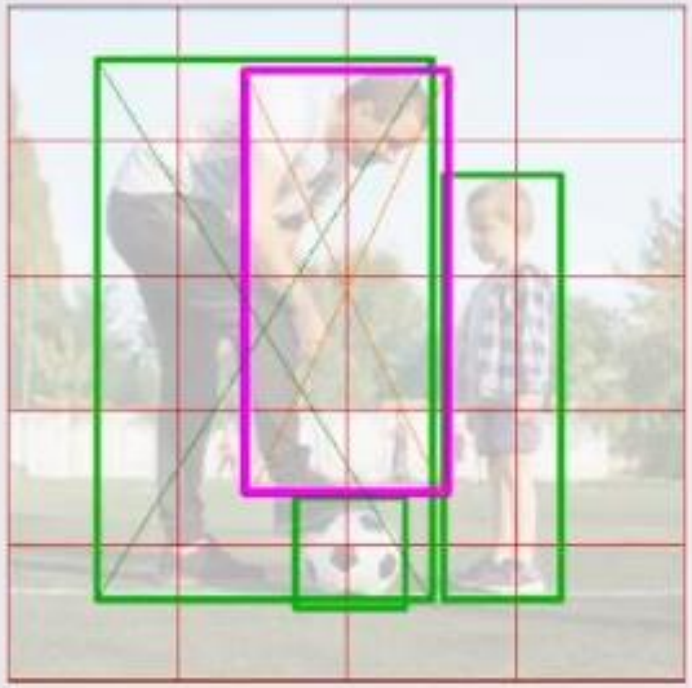
Undetermined (Mixed)

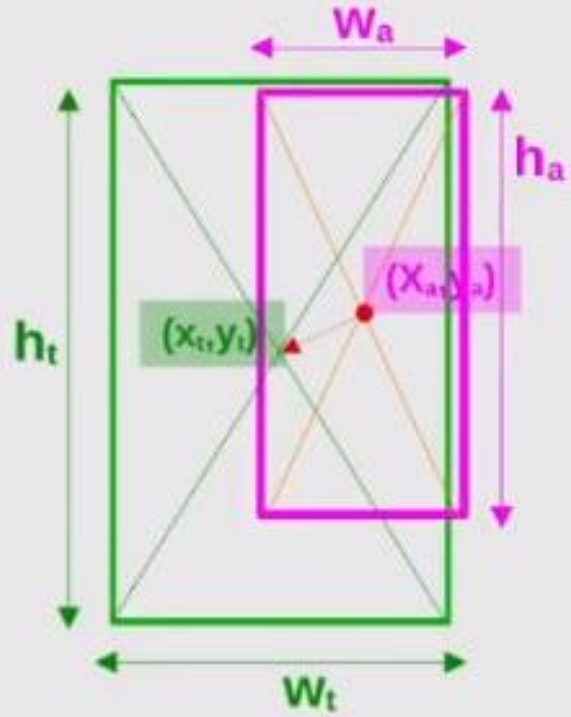
0.3 < IOU <0.7 with ALL Objects $\begin{bmatrix}0\\0\end{bmatrix}$



Object (Ground Truth)

[2] Regressor Vector of Anchor Box





Regressor Vector
contains [X,Y,W,H]
of each Anchor Box

Define Ground Truth Box (target) with

(x_t,y_t) *coordinates of the center of object*

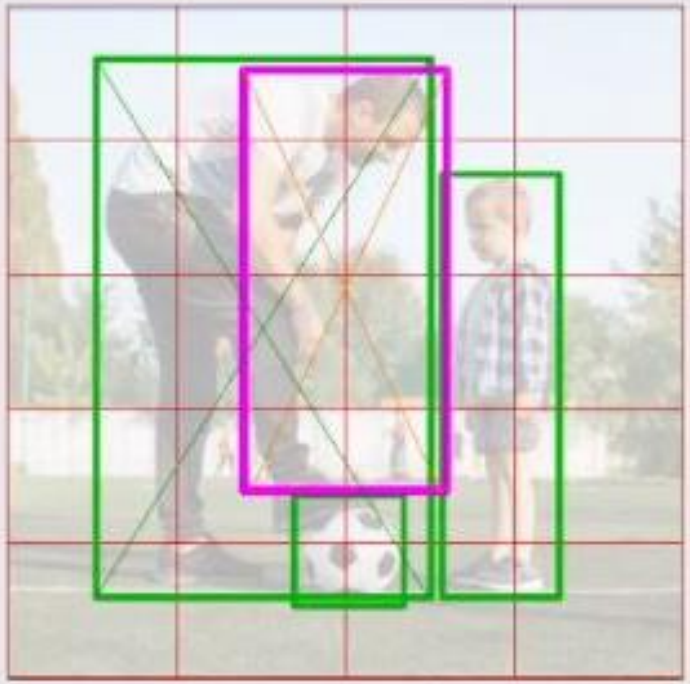
(w_t,h_t) *Width and height of Object*

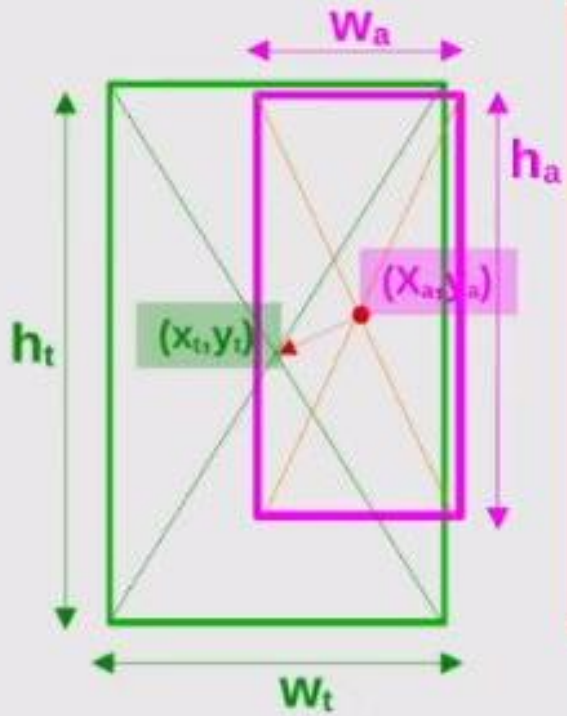
Define Anchor Box with

(x_a,y_a) *coordinates of the center of box*

(w_a,h_a) *Width and height of box*

[2] Regressor Vector of Anchor Box





To adapt Anchor Box size to fit on Object Truth Box (Target Box)

$(x_a, y_a) \rightarrow (x_t,y_t)$
displacement *is* (x_t-x_a) *and* (y_t-y_a)

$(w_a, h_a) \rightarrow (w_t,h_t)$
Scale difference *is* w_t/w_a *and* h_t/h_a

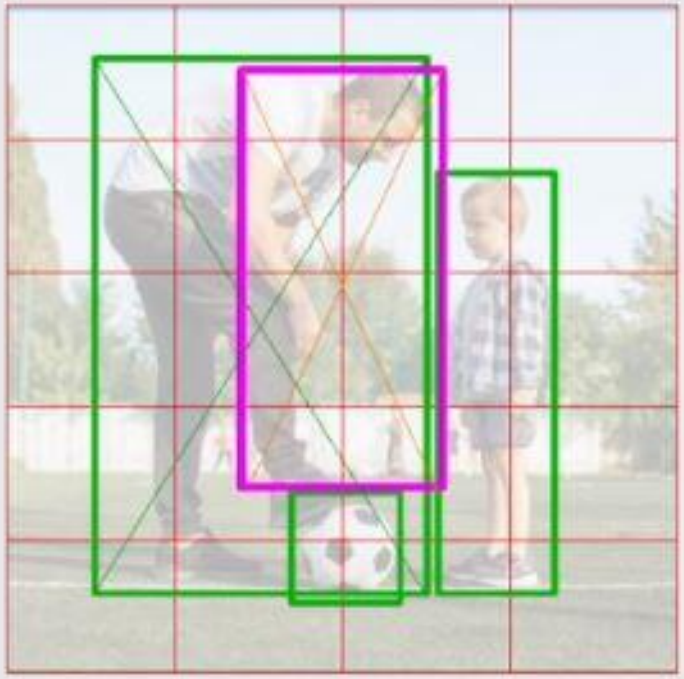
Define Ground Truth Box (target) with

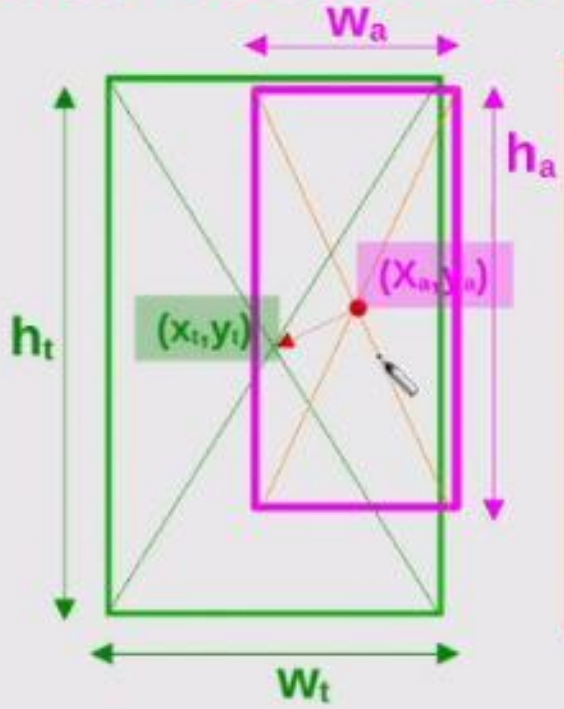
(x_t,y_t) *coordinates of the center of object*
(w_t,h_t) *Width and height of Object*

Define Anchor Box with

(x_a,y_a) *coordinates of the center of box*
(w_a,h_a) *Width and height of box*

[2] Regressor Vector of Anchor Box





To adapt Anchor Box size to fit on Object Truth Box (Target Box)

$(x_a, y_a) \rightarrow (x_t,y_t)$
displacement *is* (x_t-x_a) *and* (y_t-y_a)

$(w_a, h_a) \rightarrow (w_t,h_t)$
Scale difference *is* w_t/w_a *and* h_t/h_a

Normalize values in order to be <u>*object size independent*</u>

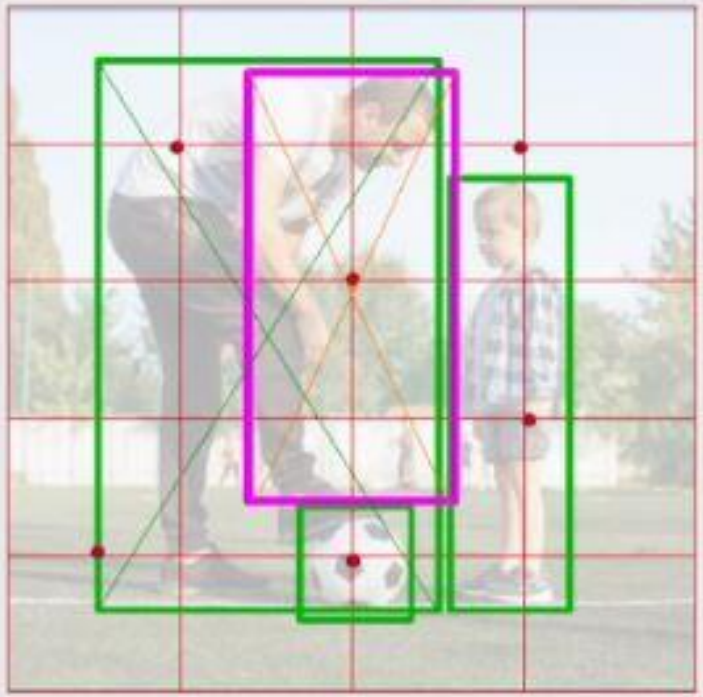
Use $d_x = (x_t-x_a)/x_a$
$d_y = (y_t-y_a)/y_a$
$d_w = w_t/w_a$
$d_h = h_t/h_a$

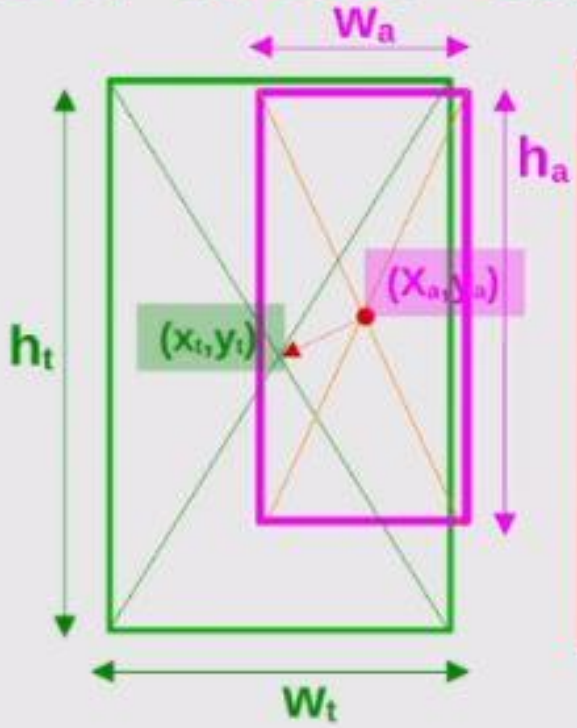
⇨

If Anchor Box fit 100% with Object box then

$d_x = 0$
$d_y = 0$
$d_w = 1$ -------??
$d_h = 1$ ------ ??

[2] Regressor Vector of Anchor Box





To adapt Anchor Box size to fit on Object Truth Box (Target Box)

$(x_a, y_a) \rightarrow (x_t,y_t)$
displacement *is* (x_t-x_a) *and* (y_t-y_a)

$(w_a, h_a) \rightarrow (w_t,h_t)$
Scale difference *is* w_t/w_a *and* h_t/h_a

Normalize values in order to be object size independent

Use $d_x = (x_t-x_a)/x_a$
$d_y = (y_t-y_a)/y_a$
$d_w = w_t/w_a$
$d_h = h_t/h_a$

⇨

If Anchor Box fit 100% with Object box then

$d_x = 0$
$d_y = 0$
$d_w = 1$ -------??
$d_h = 1$ ------ ??

Use Log function

$d_x = (x_t-x_a)/x_a$
$d_y = (y_t-y_a)/y_a$
$d_w = \log(w_t/w_a)$
$d_h = \log(h_t/h_a)$

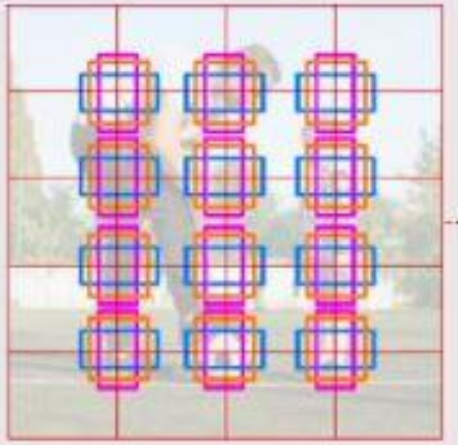
If Anchor Box fit 100% with Object box then

$d_x = 0$
$d_y = 0$
$d_w = 0$
$d_h = 0$

All Values are zeros

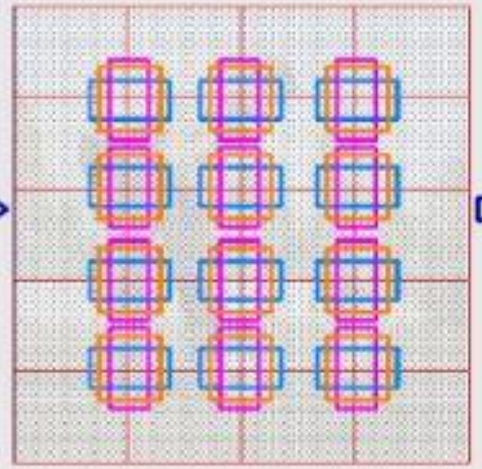
[3] RPN Training Data Preparation

[Training of RPN *(The Complete Picture)*



Labels
For ALL anchor boxes "K" at EACH anchor point:

Pre-Trained CNN Model
e.g. VGG 16



Feature Map of the whole image

Region Proposal Network (RPN)

Loss Function

*Displacement vector w.r.t overlapped Ground Truth Box (4 values * K anchor boxes) For K=9, length=36*
[Regressor Vector]

*Does it enclose Object, Background, Mix ? (2 values *K anchor boxes) For K=9, length=18*
[Objectness Vector]

Contents of anchor boxes can be extracted directly from the Feature map (instead of using Spacial domain image)

How to Prepare Training Data for RPN

1) Get a training dataset that contain images with Annotated objects (bounding boxes)

2) Use any pre-trained CNN (e.g. VGG16) to obtain the feature map of the input image

3) For each anchor point in the input image, generate coordinates for all "K" anchor boxes (centered at this anchor point)

4) Calculate IOU between those anchor boxes and ALL objects ground truth boxes.

5) Mark each anchor box as enclosing Object [1 , 0], Background only [0 , 1], or Mix [0 , 0].

This "Objectness" vector length should be "K"*2

How to Prepare Training Data for RPN

6) For anchor boxes including objects, calculate the displacement vector (4 values) between the anchor box and corresponding object box.

7) For other anchor boxes, fill the values with zeros. (will not be used). This "Regression" vector length should be "K"*4

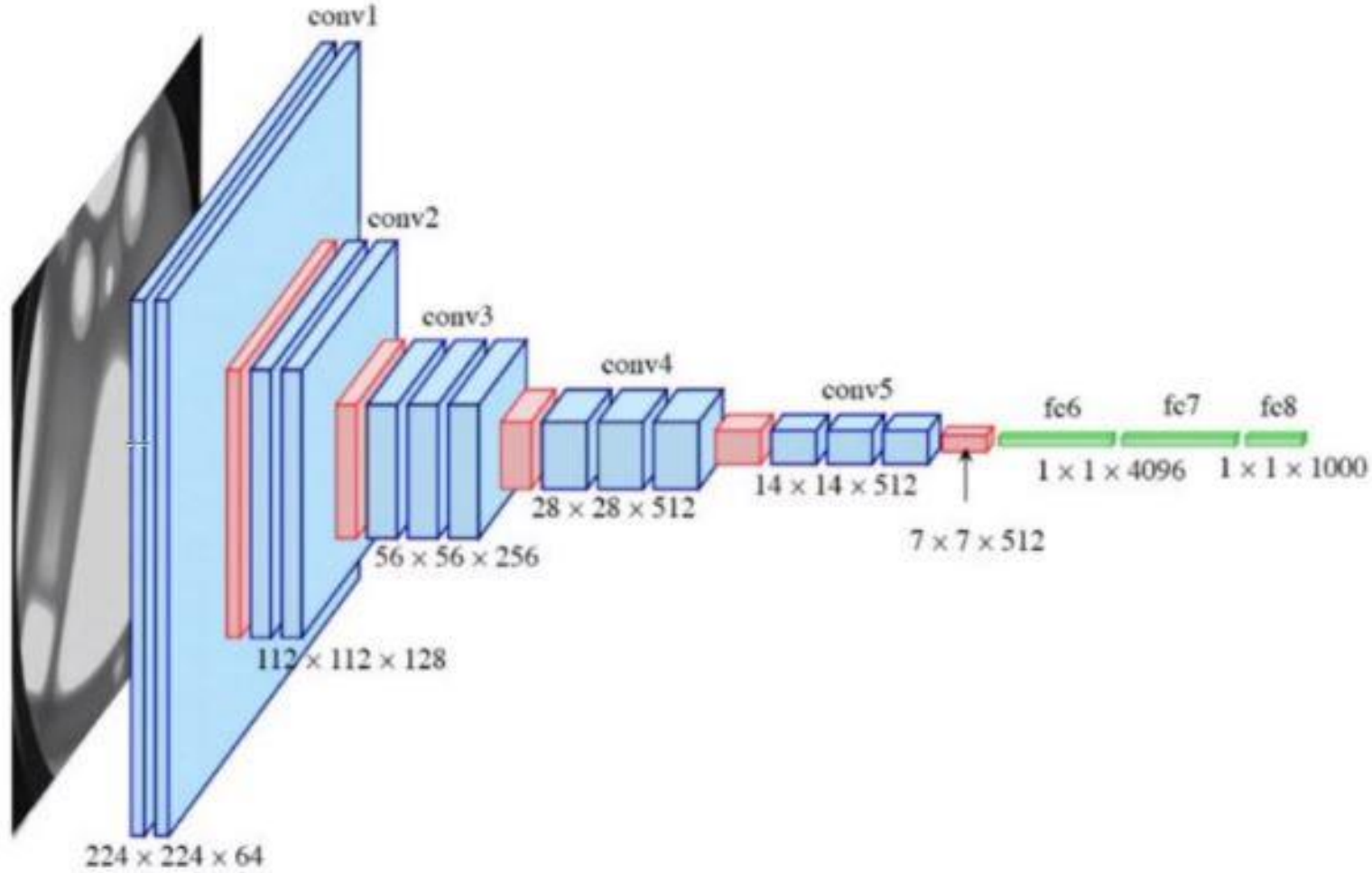
8) Provide RPN with both feature map (as Input) and "Objectness & Regression" vectors (for each anchor point) as Label.

[4] Quick Review of VGG 16

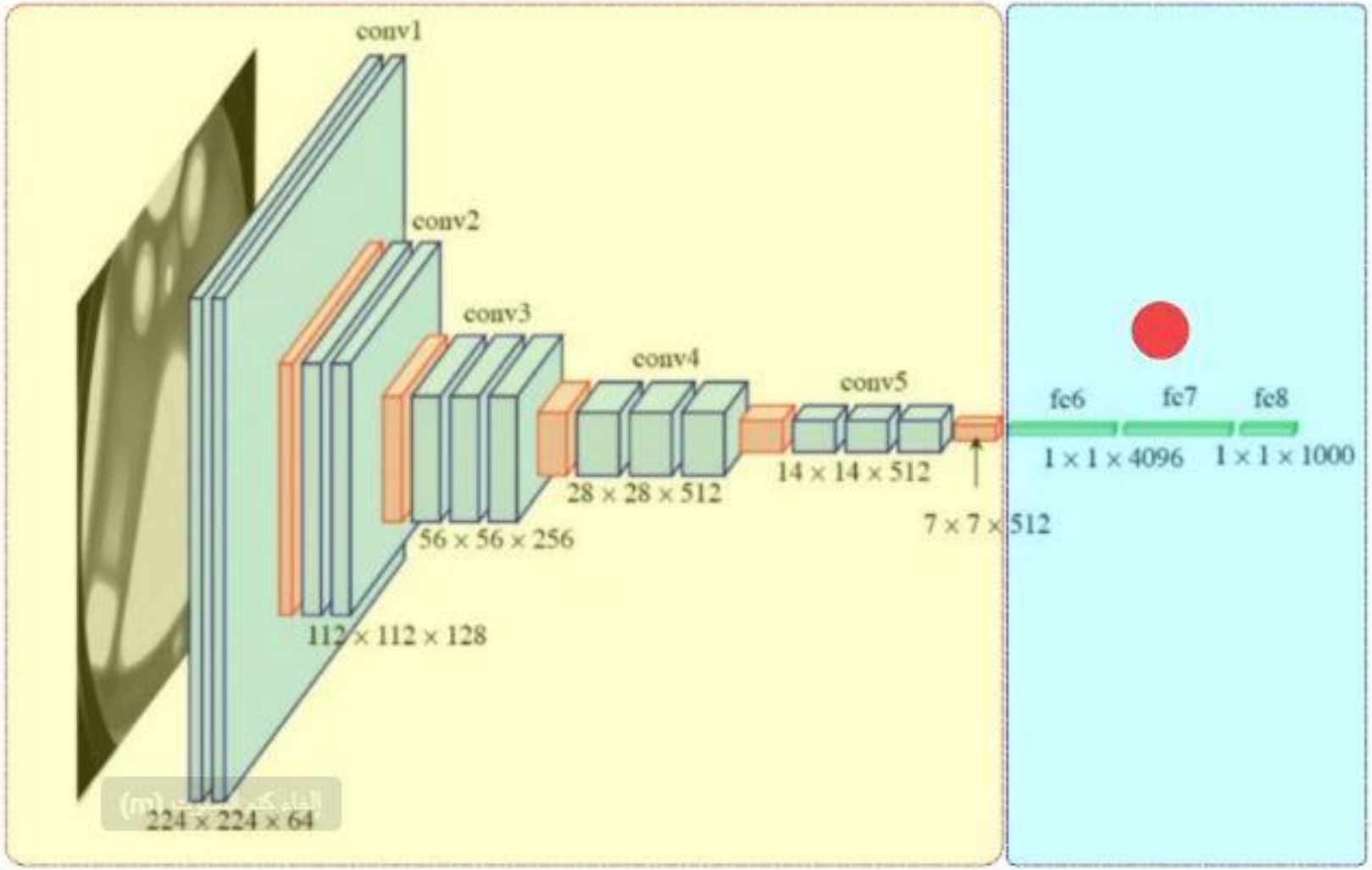
(to Generate Feature Map of Input Image)

(One may use any other CNN network as AlexNet, ResNet,..)

VGG 16 Architecture



VGG 16 Architecture



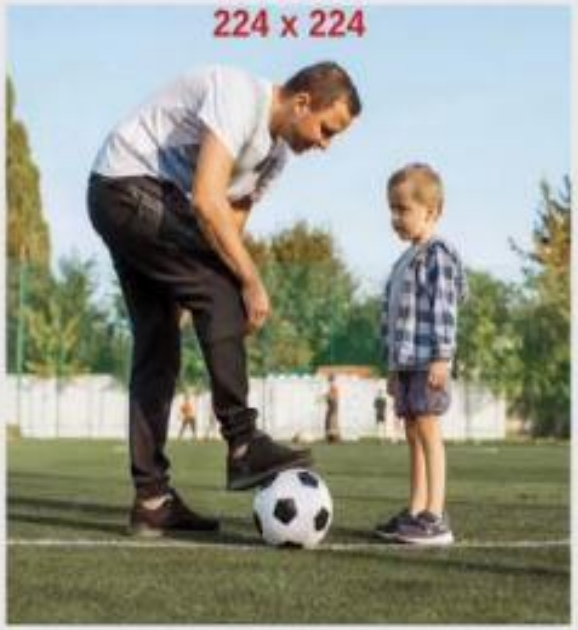
Convolution Part of VGG16	
Input Image	224x224x3
Conv1: 64 filters	224x224x64
Pool	112x112x64
Conv2: 128 filters	112x112x128
Pool	56x56x128
Conv3: 256 filters	56x56x256
Pool	28x28x256
Conv4: 512 filters	28x28x512
Pool	14x14x512
Conv5: 512 filters	14x14x512
Pool	**7x7x512**

convolution+ReLU
max pooling
fully connected+ReLU

[5] How to Apply 1x1 Convolution

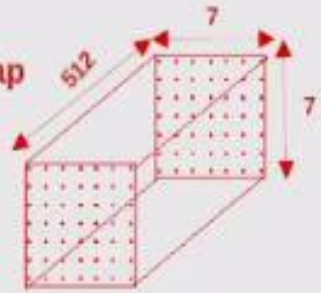
to obtain

Regressor and Objectness Vectors



VGG 16
Pre-Trained CNN Model

7x7x512
Feature map



Output of **Last** Conv Layer

VGG 16
Pre-Trained CNN Model

7x7x512
Feature map

Output of **Last** Conv Layer

Feature map generated from VGG 16 Last Conv Layer

Vectors of length 512

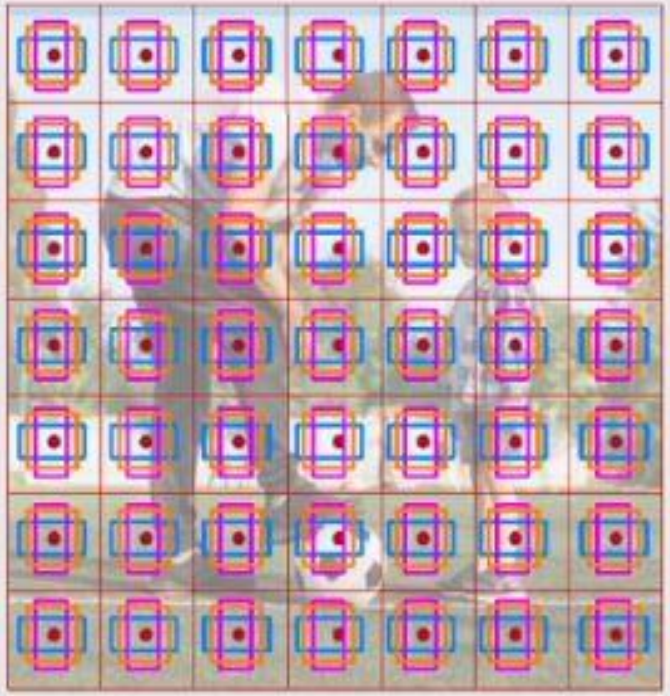
512

7

Each Vector of size 1x1x512
Is representing feature map
of block With size 224/7 x 224/7
From the input image

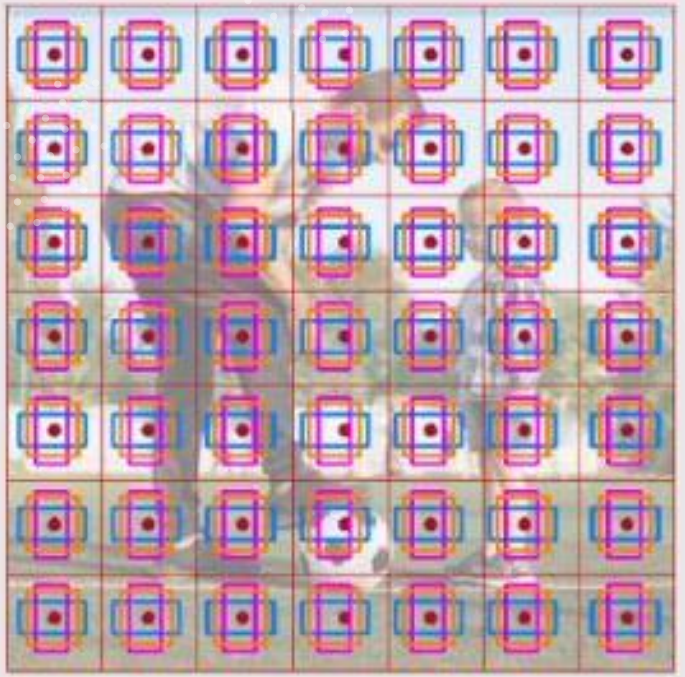
Remember:

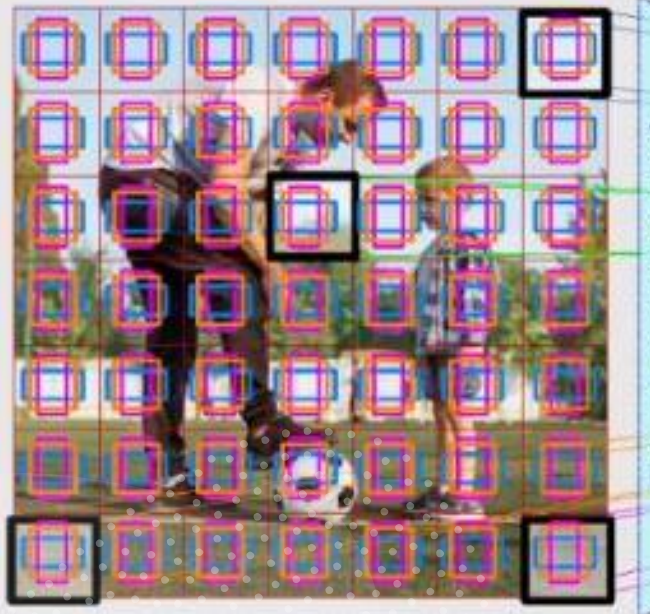
- Input Image is divided into Cells (e.g. 7x7 cells as last Conv layer of VGG16)
- Center of each cell is an Anchor Point
- Each anchor point is associated with "K" anchor boxes (K=9 in the paper)



Remember:

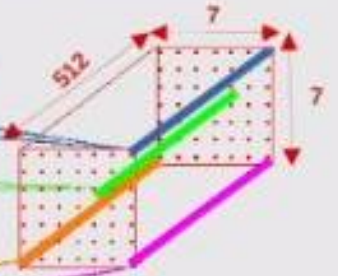
- Input Image is divided into Cells (e.g. 7x7 cells as last Conv layer of VGG16)
- Center of each cell is an Anchor Point
- Each anchor point is associated with "K" anchor boxes (K=9 in the paper)





Feature map generated from VGG 16 Last Conv Layer

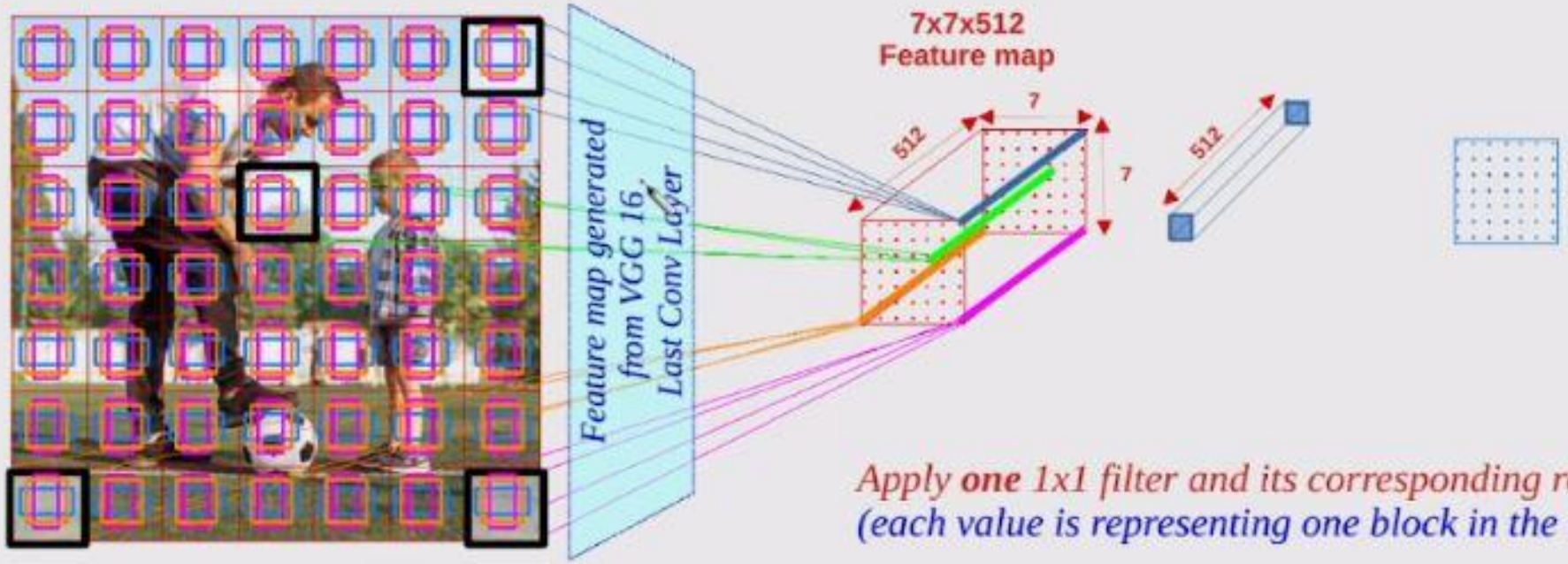
7x7x512
Feature map



Each Vector of size 1x1x512
Is representing feature map
Of block covered by **"K" Anchor Boxes**
(Corresponding to one Anchor Point)

Apply 1x1 Convolution filter(s)

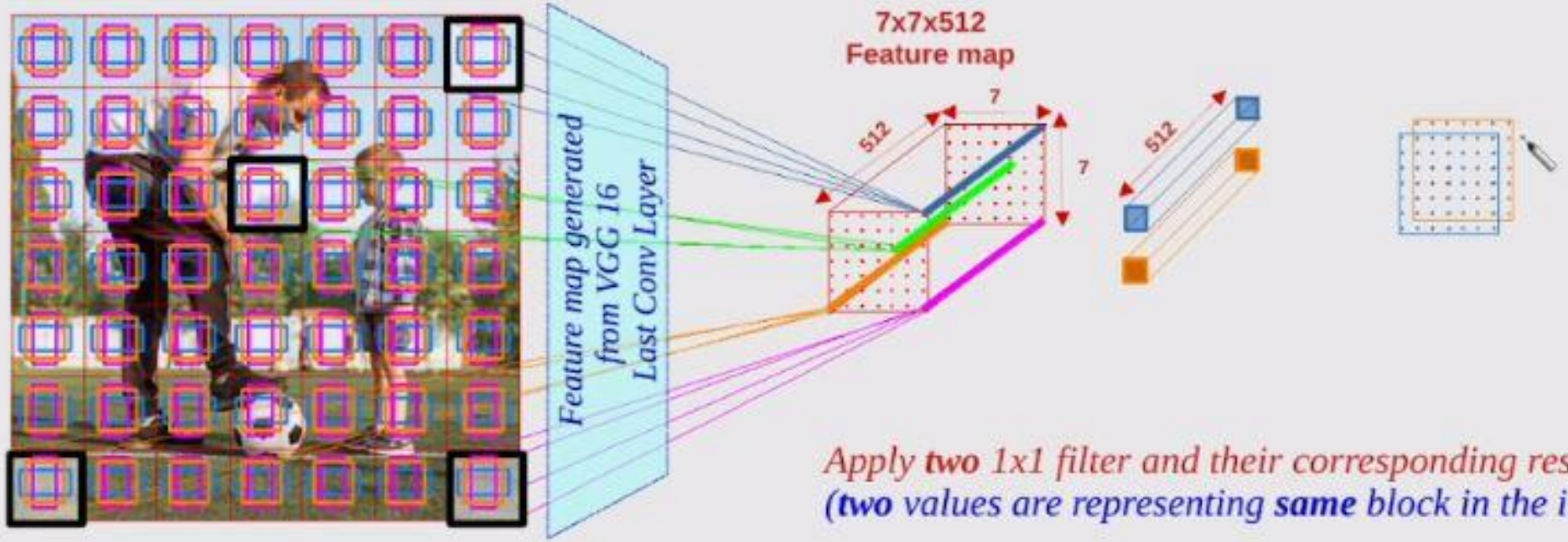
(on the feature map of last VGG Conv layer)



*Apply **one** 1x1 filter and its corresponding response*
(each value is representing one block in the image)

Apply 1x1 Convolution filter(s)

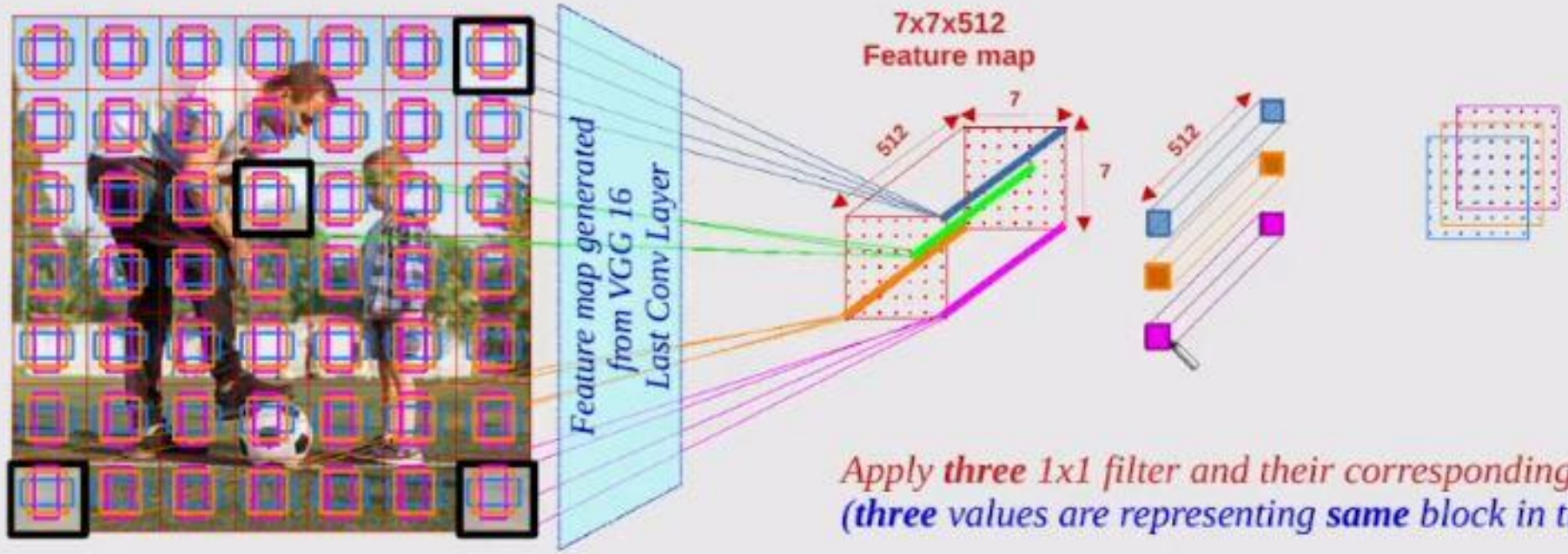
(on the feature map of last VGG Conv layer)



*Apply **two** 1x1 filter and their corresponding responses*
*(**two** values are representing **same** block in the image)*

Apply 1x1 Convolution filter(s)

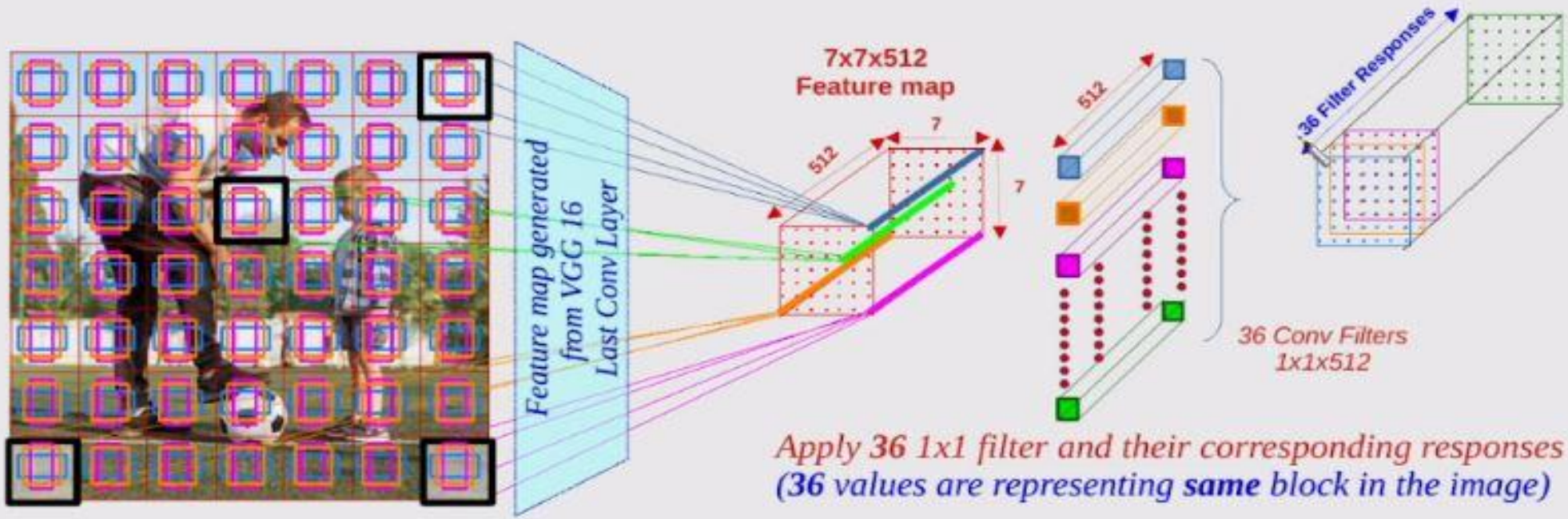
(on the feature map of last VGG Conv layer)



*Apply **three** 1x1 filter and their corresponding responses*
*(**three** values are representing **same** block in the image)*

Apply 1x1 Convolution filter(s)

(on the feature map of last VGG Conv layer)



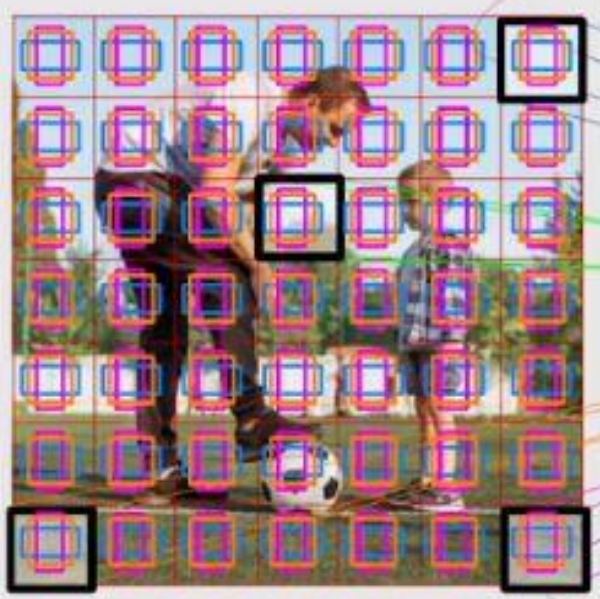
*Apply **36** 1x1 filter and their corresponding responses*
*(**36** values are representing **same** block in the image)*

Apply 1x1 Convolution filter(s)

(on the feature map of last VGG Conv layer)

Generated **49** Vectors
(there are 7 x 7 Anchor points)

Each vector of length **36**
(=9 boxes * 4 parameters)



36 values derived from this area (covered by 9 anchor boxes)

Feature map generated from VGG 16 Last Conv Layer

7x7x512 Feature map

512

7

7

512

36 Filter Responses

36 Conv Filters 1x1x512

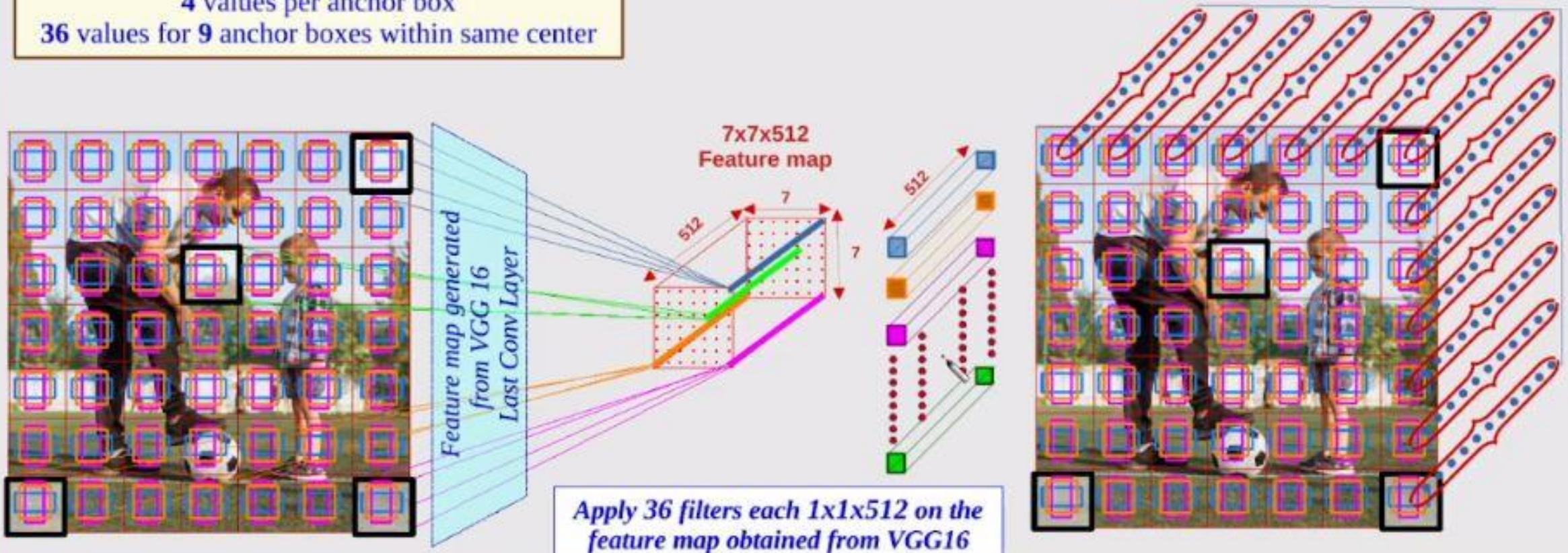
36 values derived from this area (covered by 9 anchor boxes)

Apply 1x1 Convolution filter(s)

(on the feature map of last VGG Conv layer)

Regressor Vectors
4 values per anchor box
36 values for **9** anchor boxes within same center

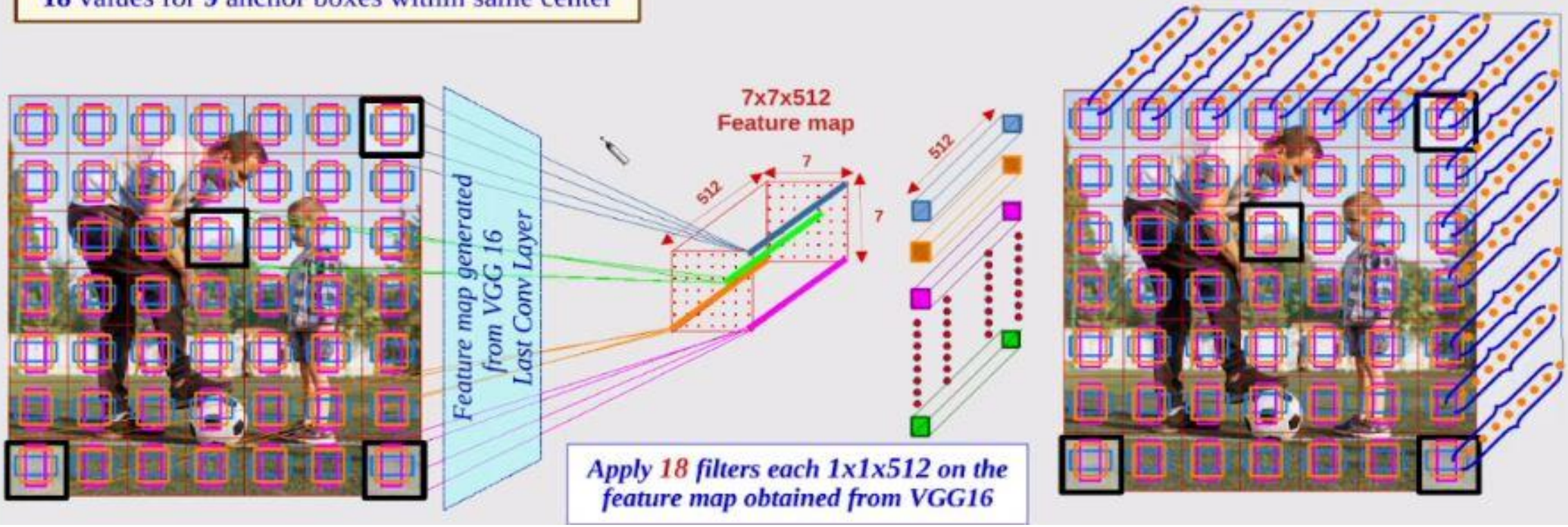
7x7 vectors each of 36 values
Each vector is derived from one area
(covered by 9 anchor boxes)



Apply 1x1 Convolution filter(s)
(on the feature map of last VGG Conv layer)

Objectness Vectors
2 values per anchor box
18 values for **9** anchor boxes within same center

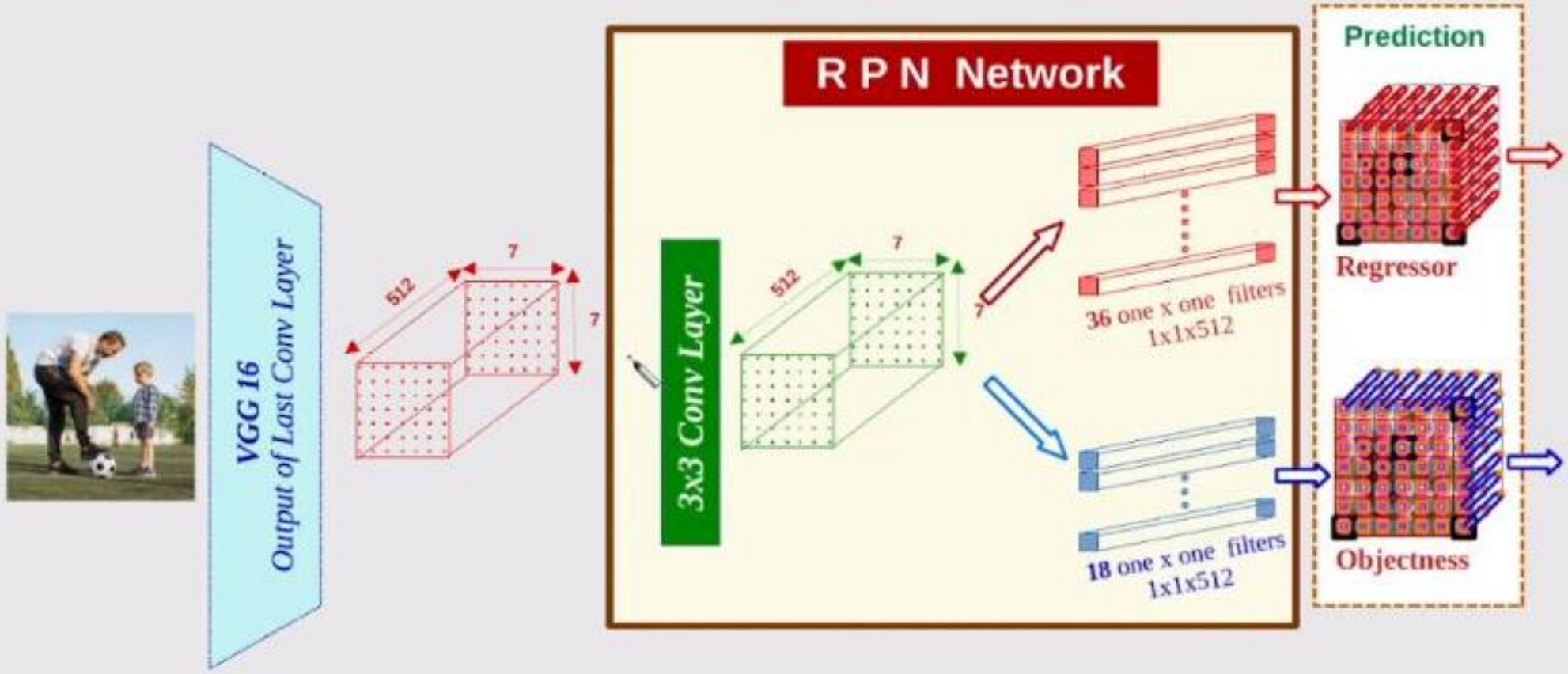
7x7 vectors each of 18 values
Each vector is derived from one area
(covered by 9 anchor boxes)



[6] RPN Architecture

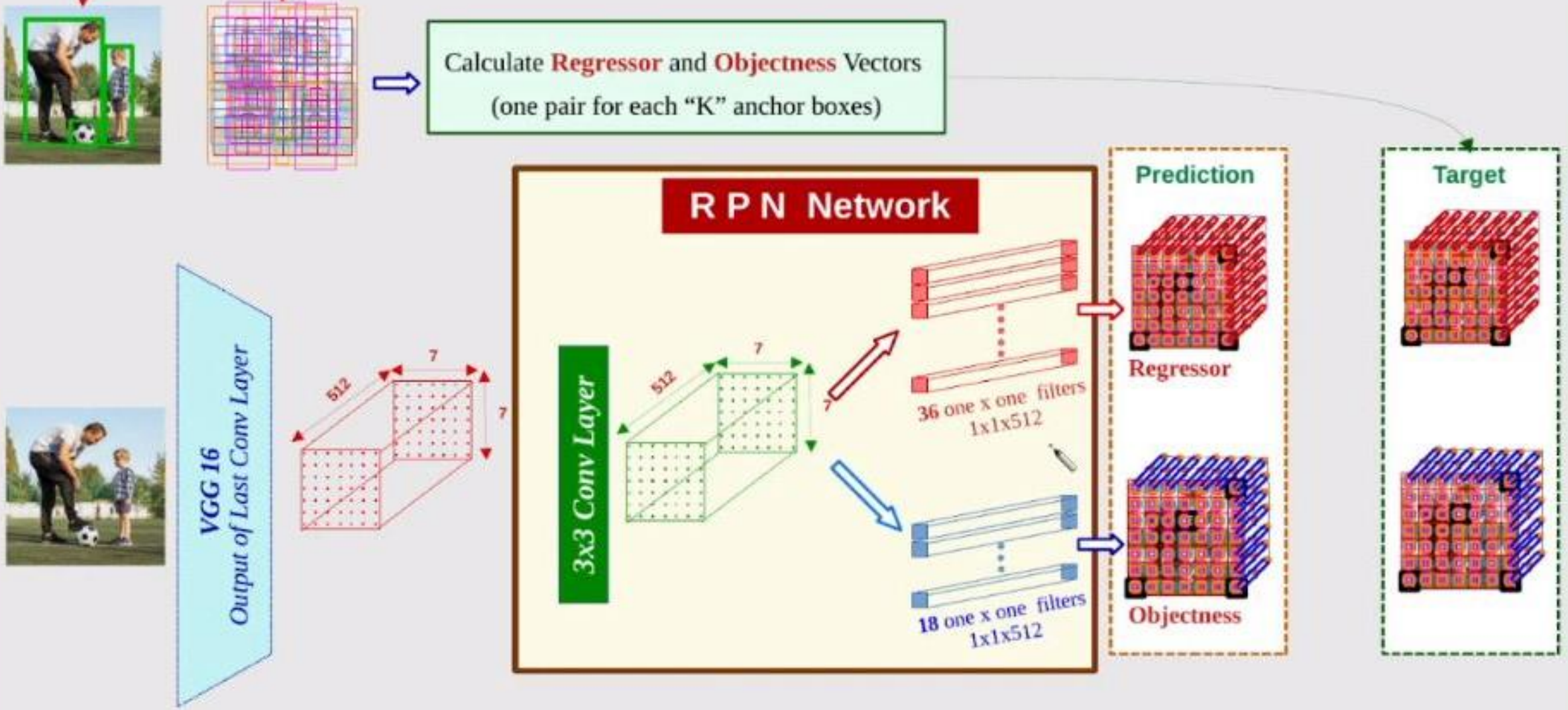
RPN Architecture

(The Full Picture – Based on VGG 16 and K=9 anchor boxes)



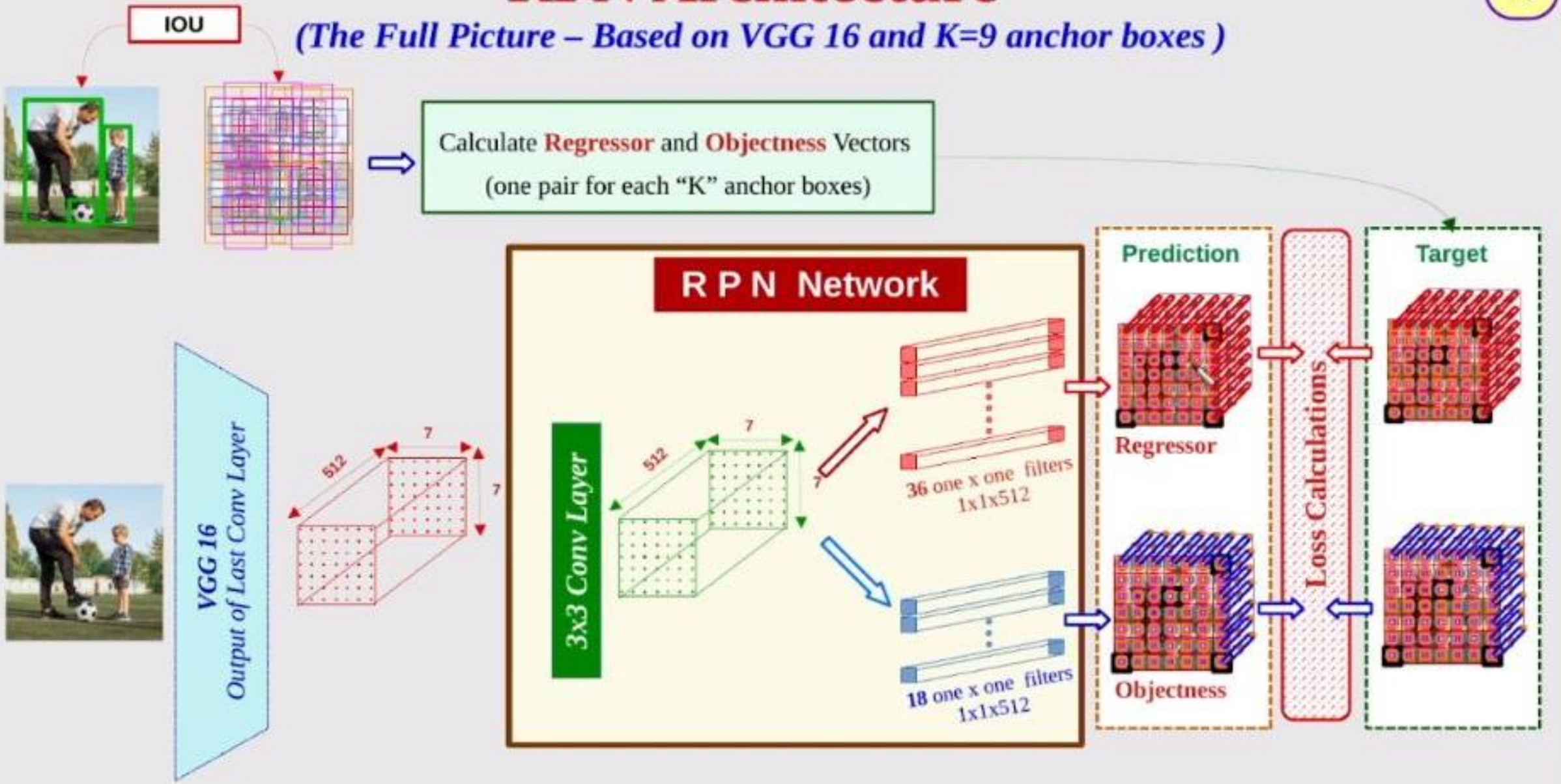
RPN Architecture

(The Full Picture – Based on VGG 16 and K=9 anchor boxes)



RPN Architecture

(The Full Picture – Based on VGG 16 and K=9 anchor boxes)



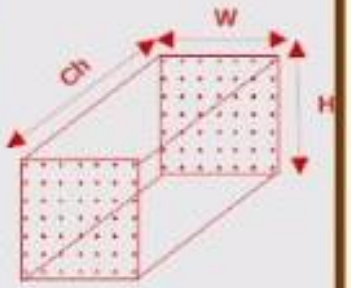
RPN Architecture

(The Full Picture – Generic Pre-trained CNN and K anchor boxes)

IOU

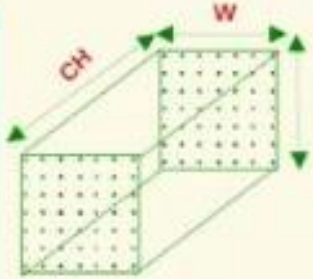
Calculate **Regressor** and **Objectness** Vectors
(one pair for each "K" anchor boxes)

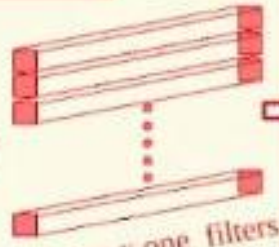
A Pre-Trained CNN Model (VGG, Alex, ResNet,...)

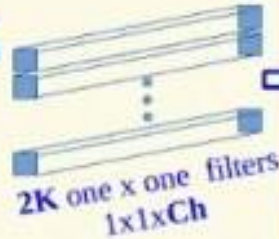


R P N Network

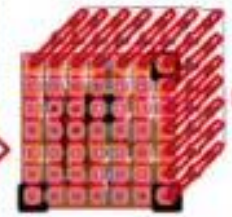
3x3 Conv Layer



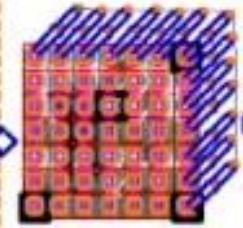




Prediction



Regressor



Objectness

Loss Calculations

Target