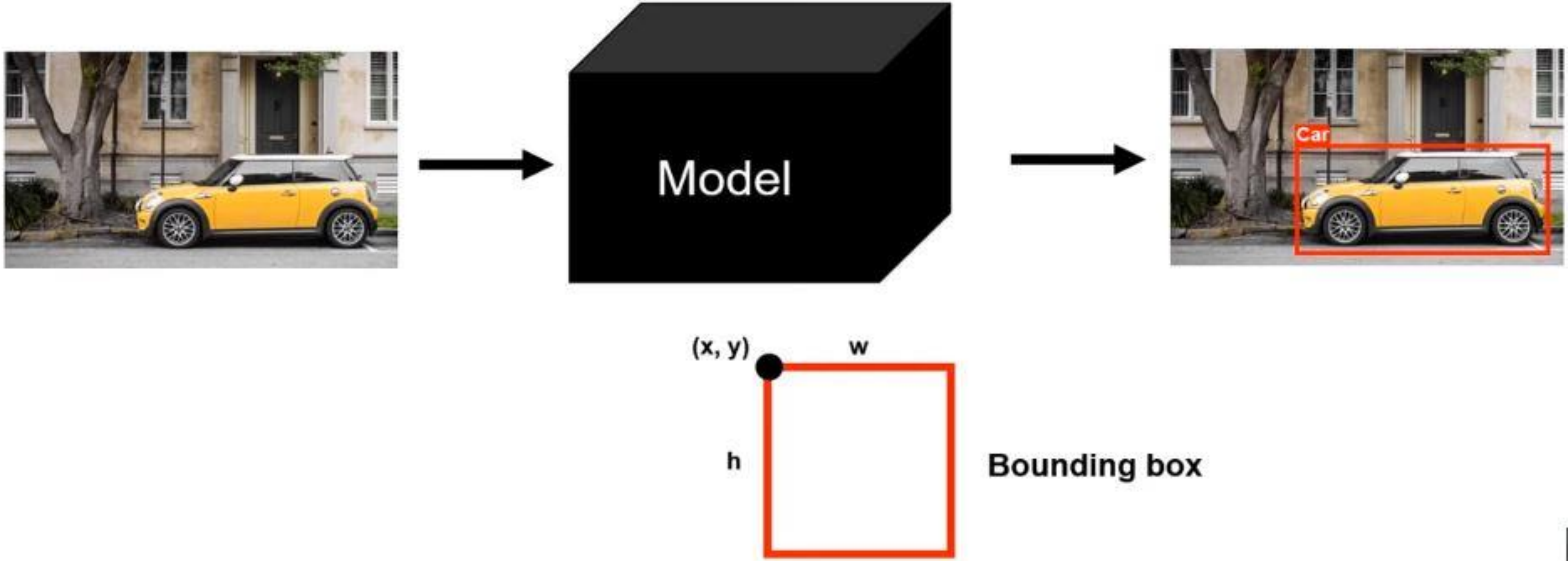
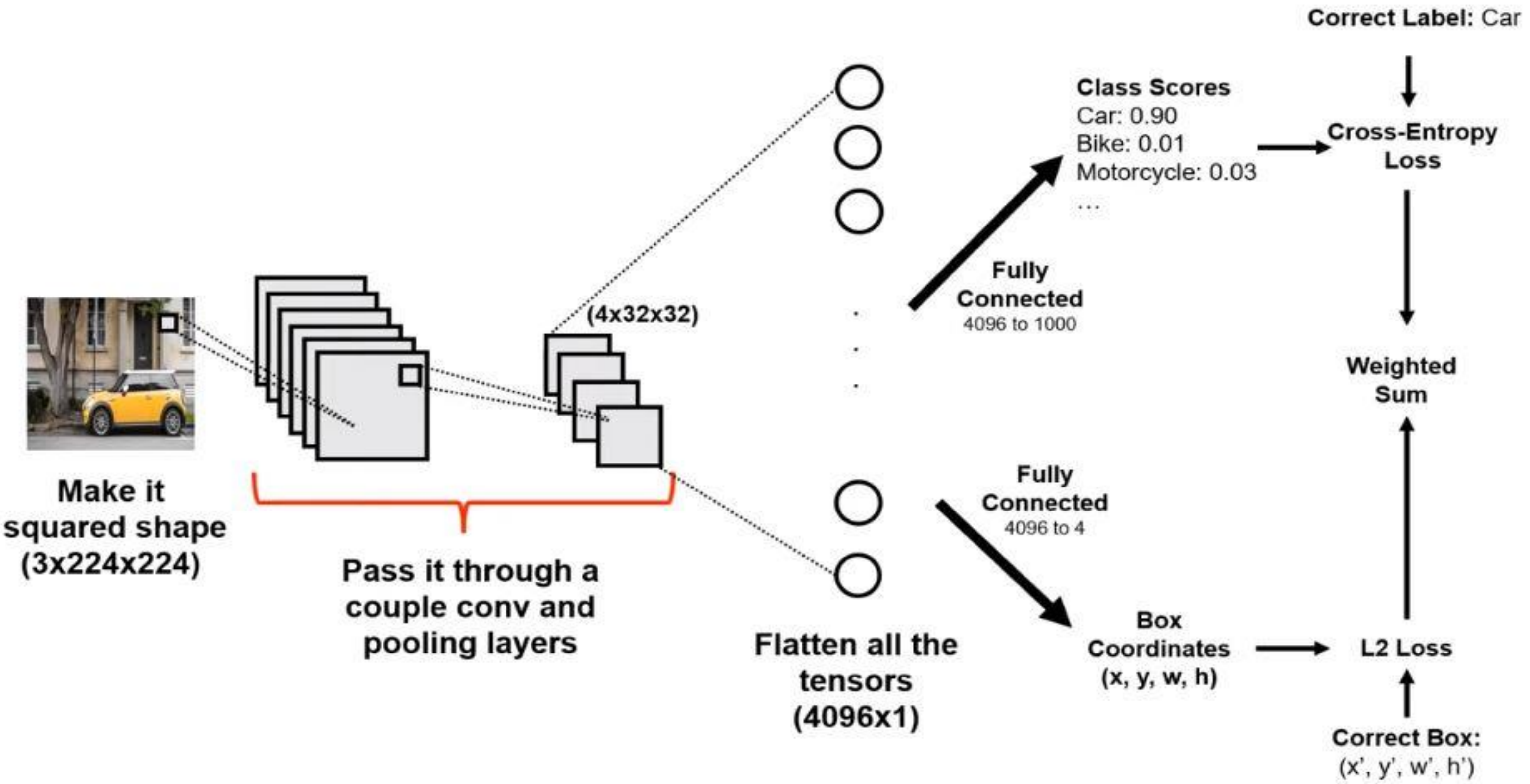

R-CNN
Car

Our Goal

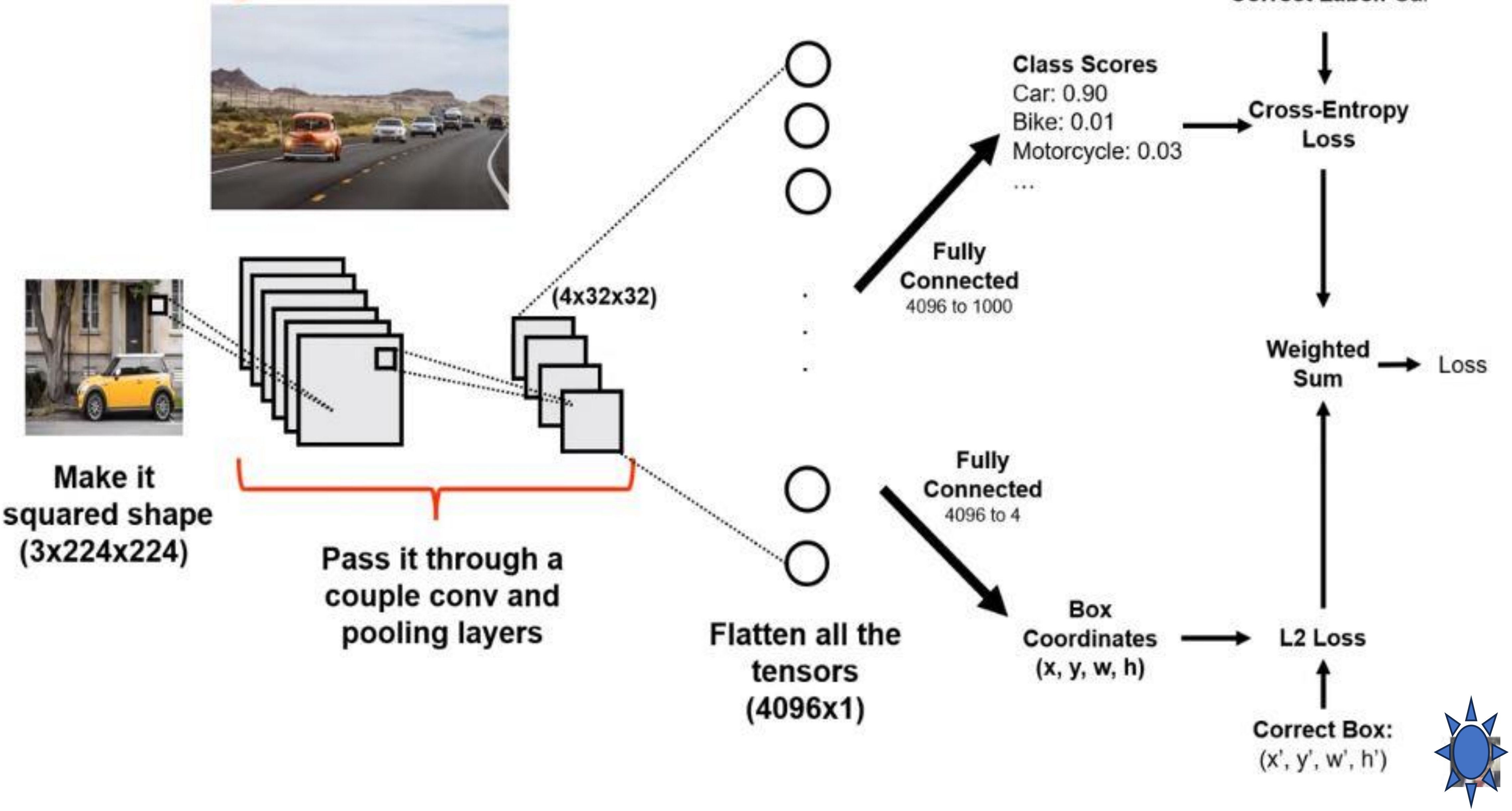


We receive input image



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)
Fully Connected
4096 to 4
Pass it through a couple conv and pooling layers
Flatten all the tensors (4096x1)
Box Coordinates (x, y, w, h)
L2 Loss
Correct Box:
(x', y', w', h')

Disadvantage: Only one object can be detected :(

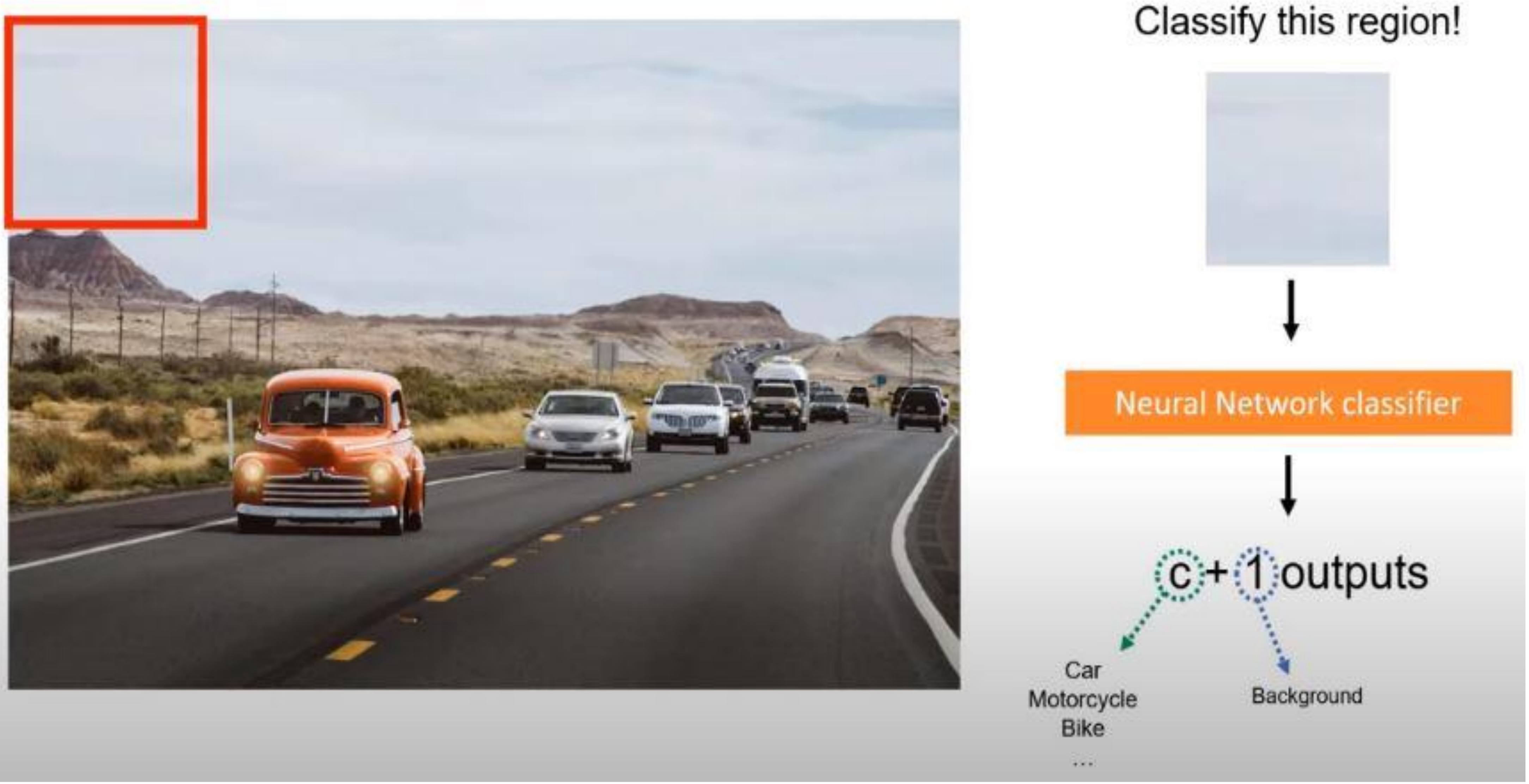


Earliest Approach

Earliest Approach

Sliding Window

Earliest Approach



Earliest Approach

Classify this region!

Neural Network classifier

Mountain

Earliest Approach

Classify this region!

Neural Network classifier

Car

Earliest Approach

W

H

w

h

Possible Positions:

$(W - w + 1) * (H - h + 1)$

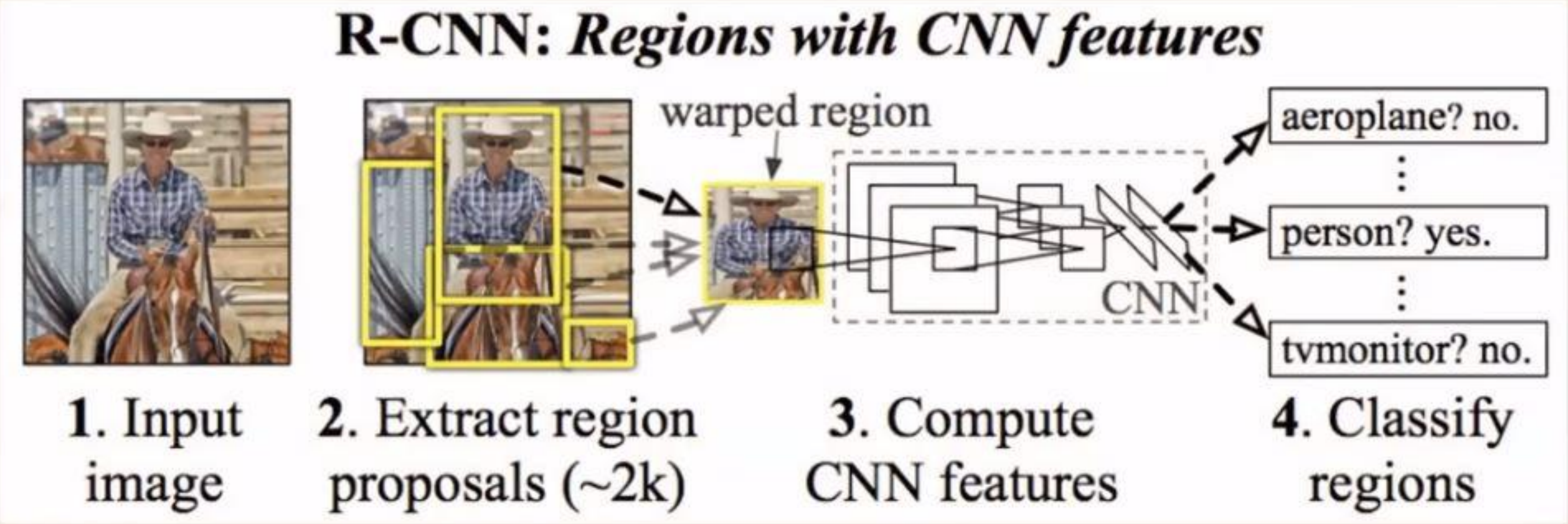
CNN as feature extractor

- 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



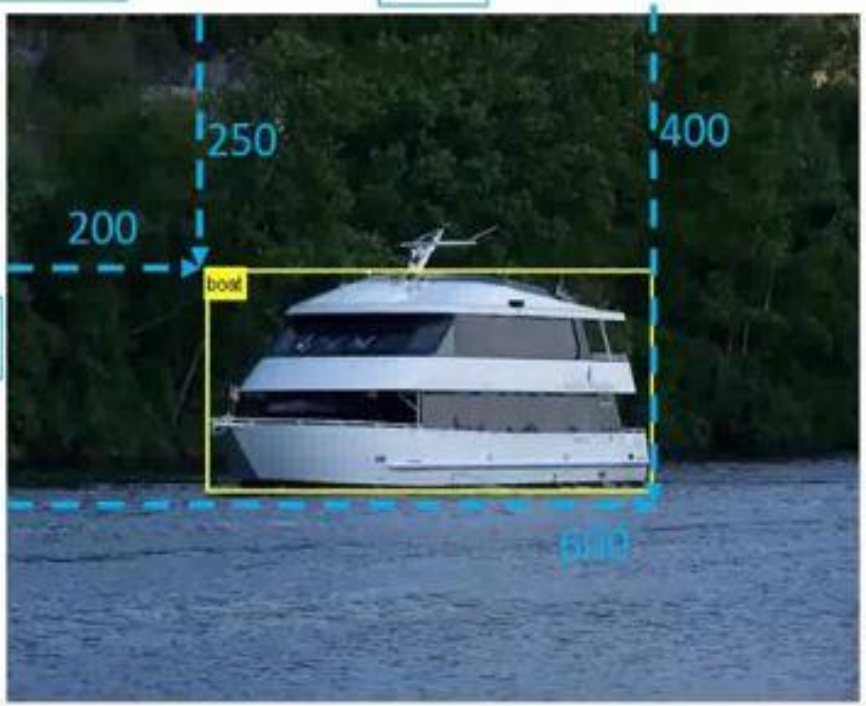
(Girshick, et al., 2014)

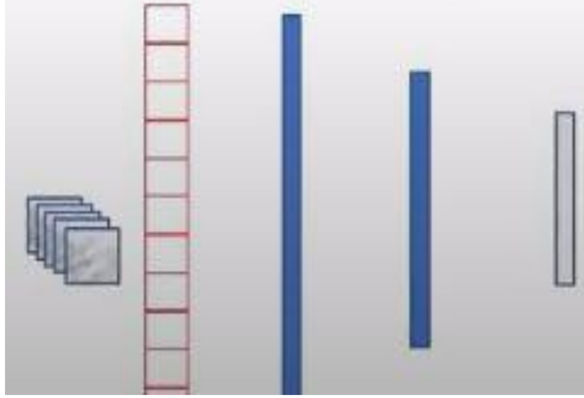
Bounding Box Regression Training

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

800

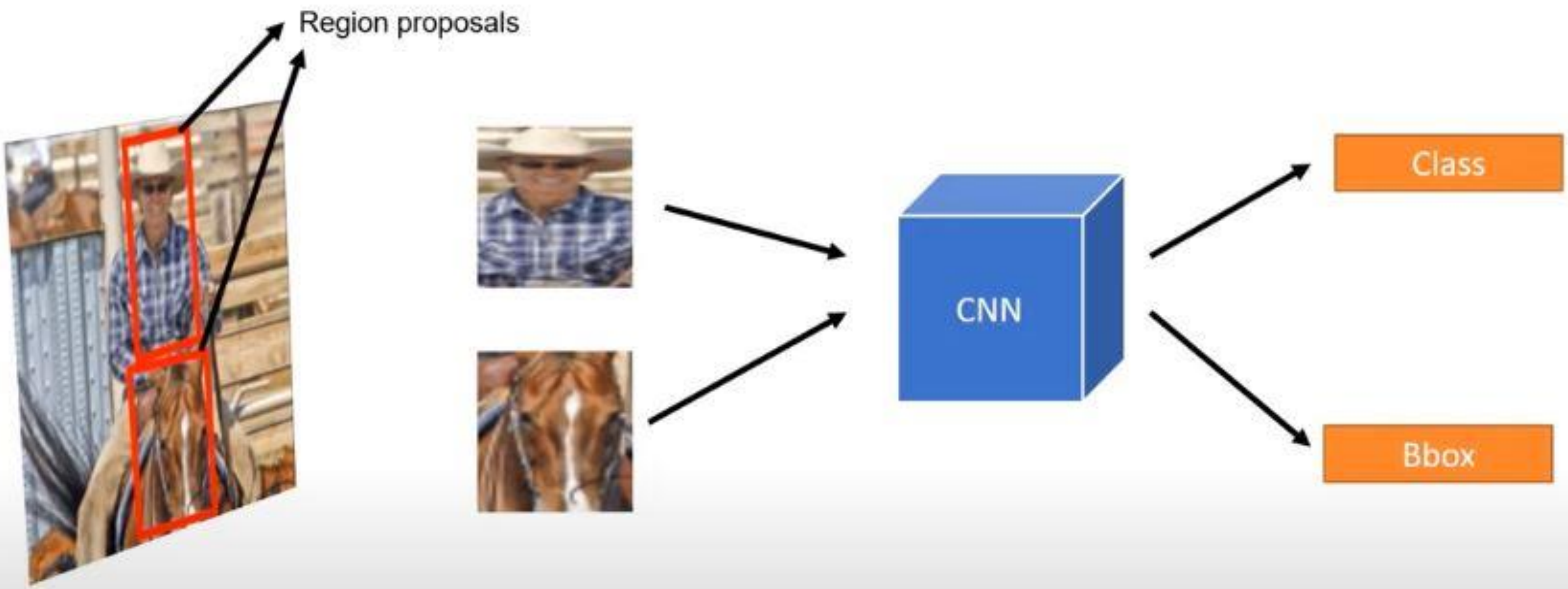
600





	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)

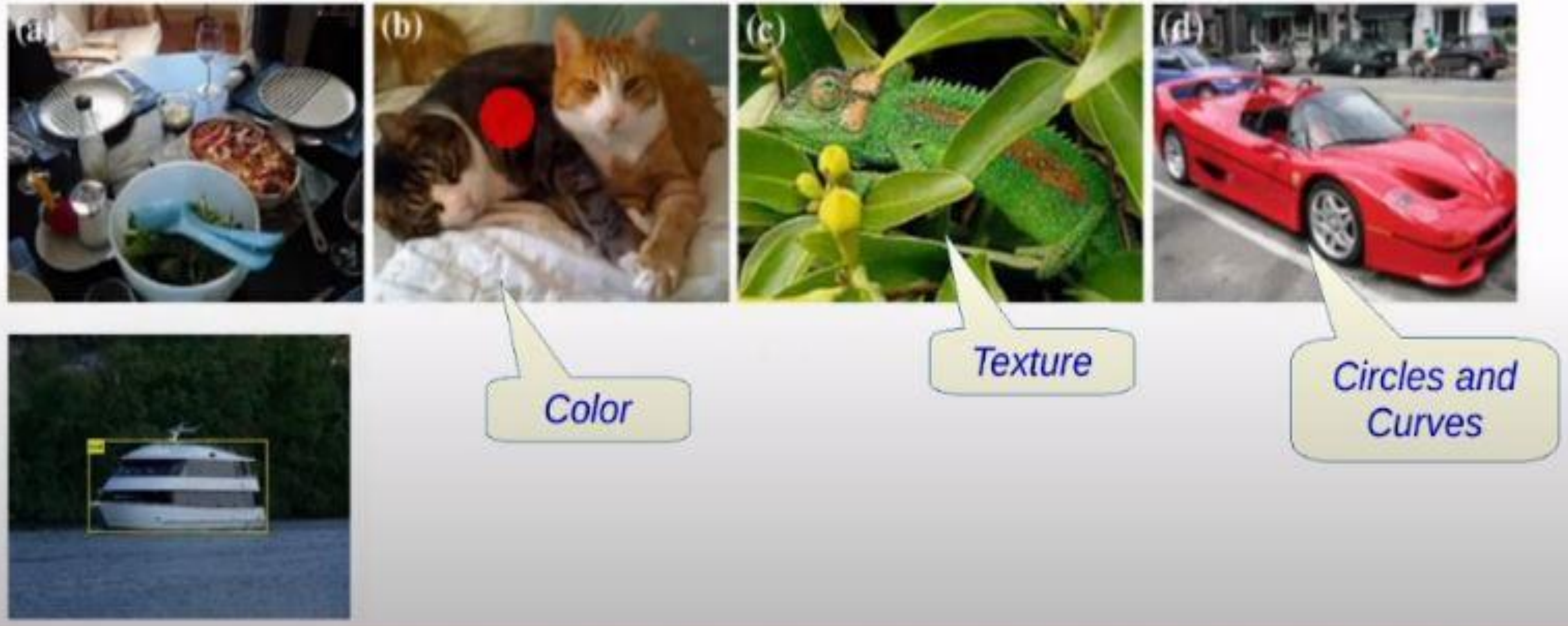
$$b_h = p_h \exp(t_h)$$

(Vertical scale)

Region Based CNN

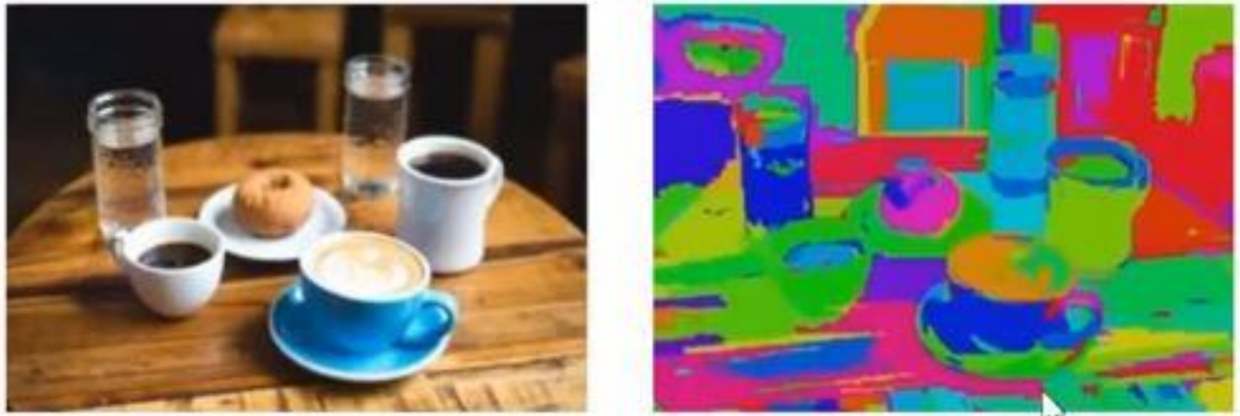
R-CNN (Region proposal + CNN)

Selective Search



Selective Search (simplified)

- Group based on intensity of the pixels.

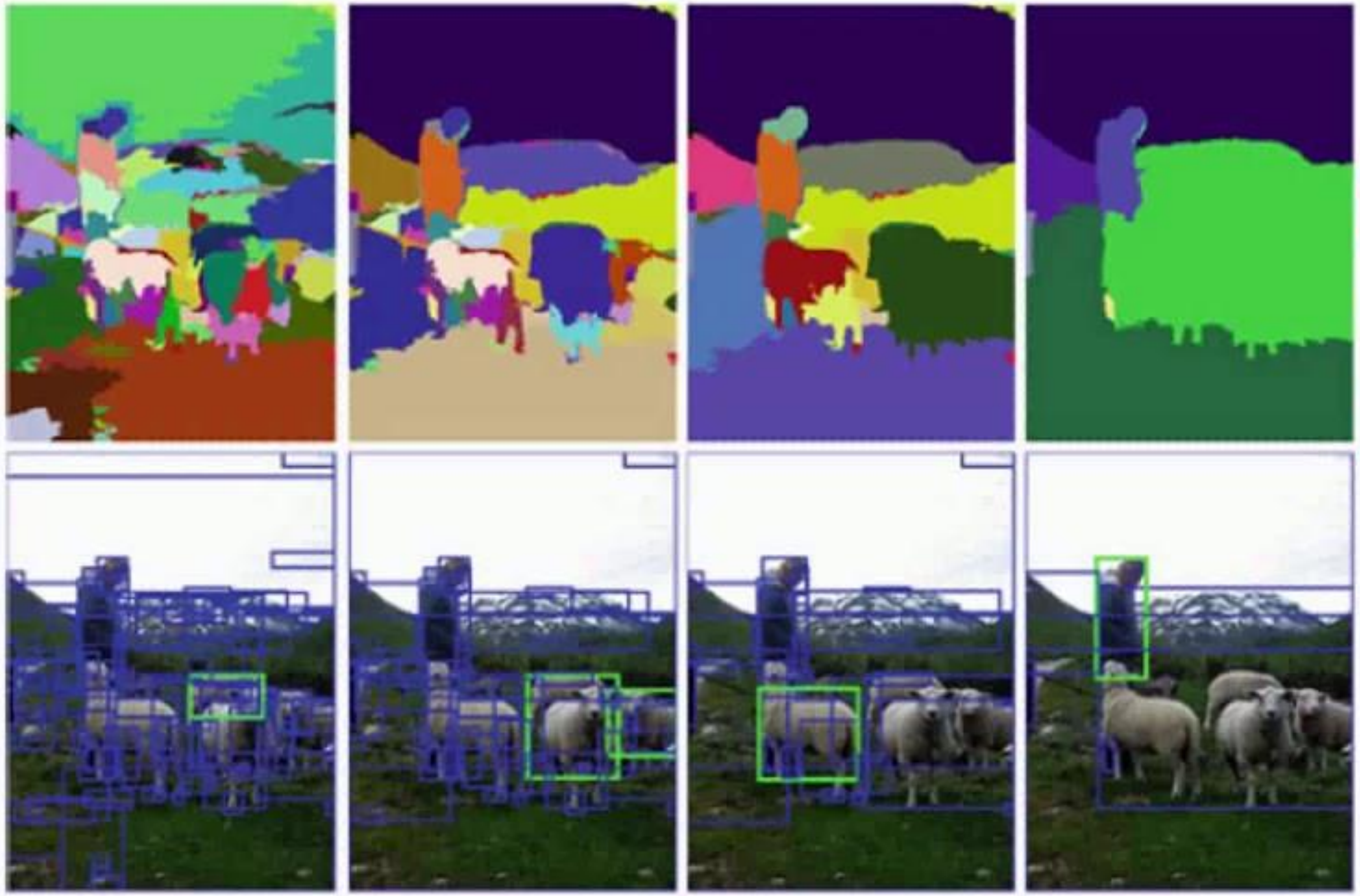


Input Image Output Image

(Chandel, 2017)

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

Region Proposal Techniques



Superpixels Straddling

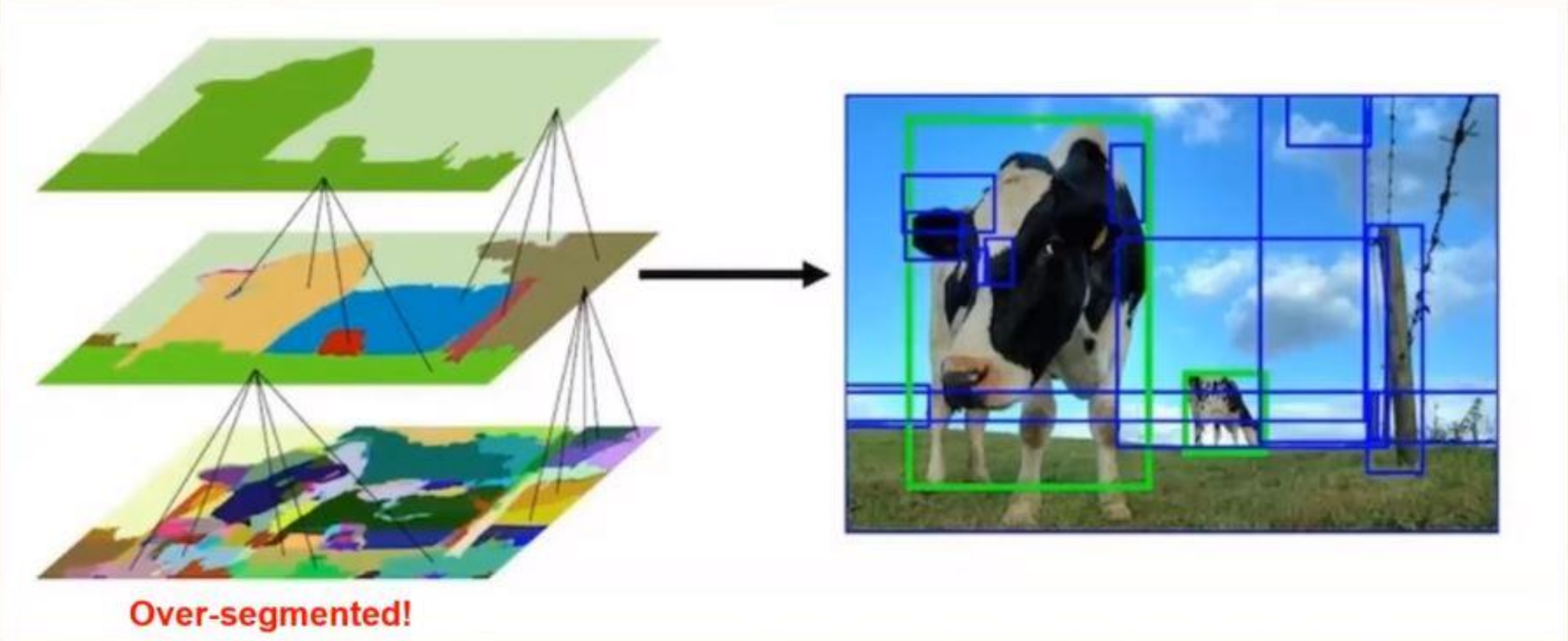
1

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

2 3 4

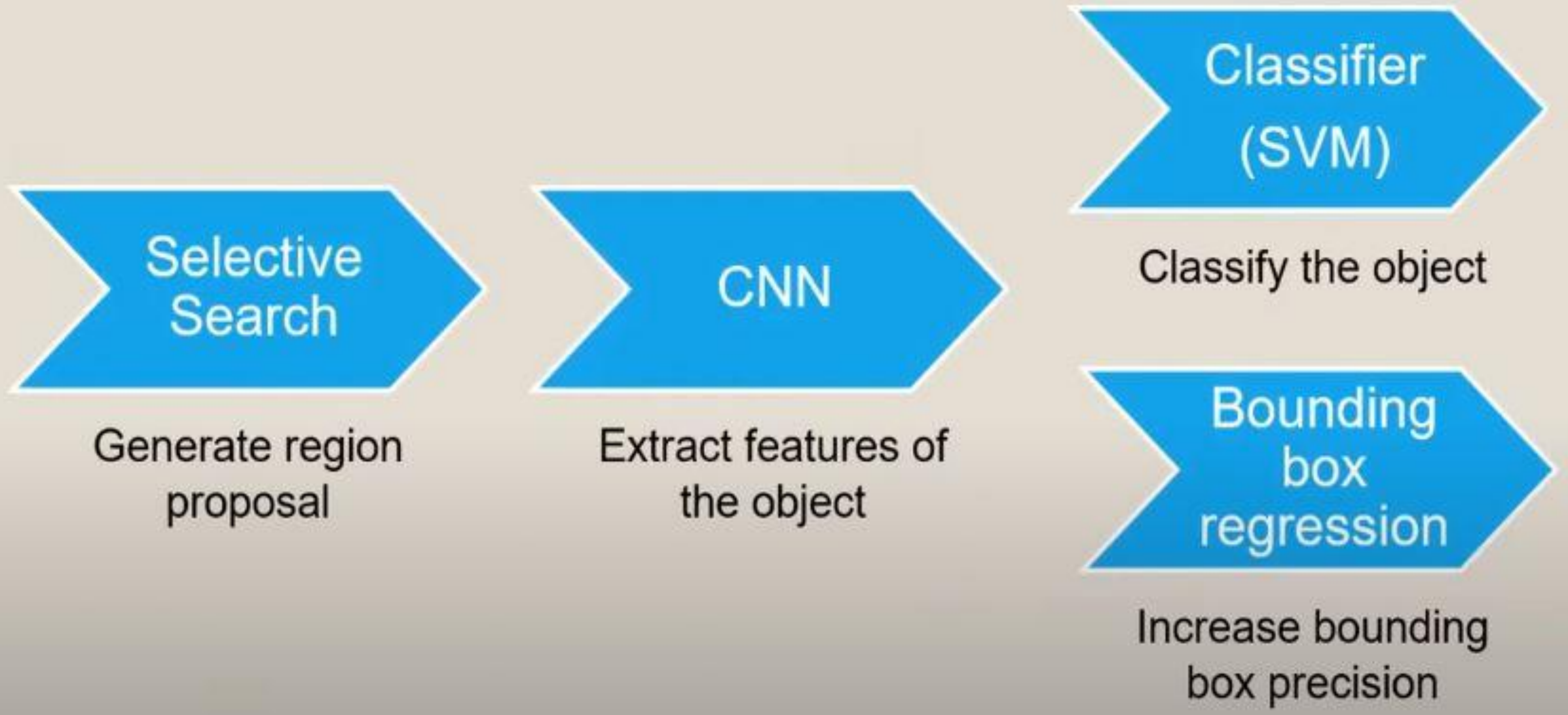
Selective Search for Object Recognition J. R. R. Uijlings, K. E. A. van de Sande, T. Gevers, A. W. M. Smeulders

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

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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

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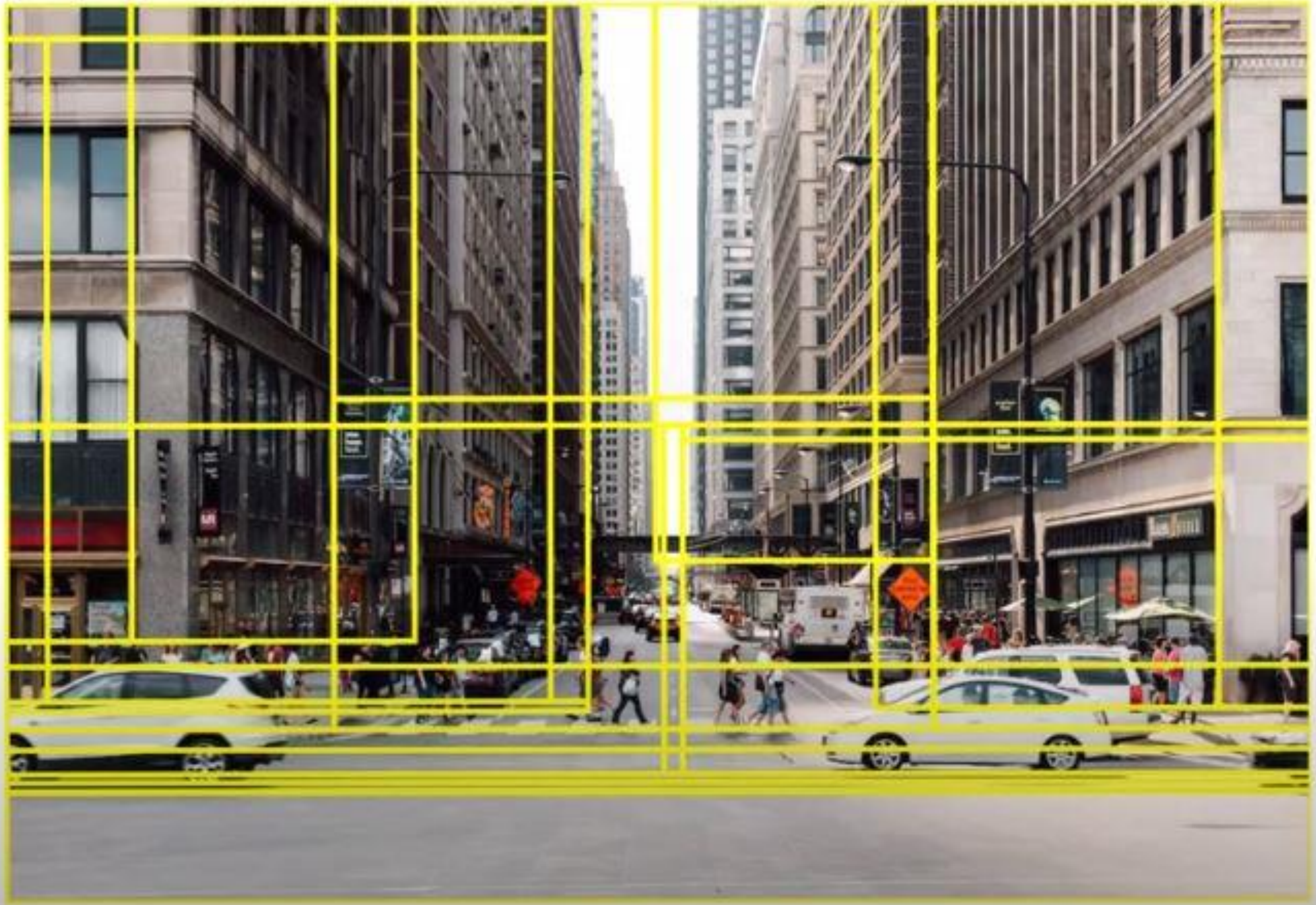

Last time: R-CNN

It is just extracting features

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

RoI Pooling

60	96	72	88	35	62	5	96
66	7	86	44	21	2	51	38
61	9	50	1	7	43	45	18
72	63	69	76	63	73	80	79
43	1	12	69	91	8	27	94
19	16	60	44	43	79	35	44
66	1	83	45	49	66	32	25
96	29	27	34	85	25	70	51

$h = 4$ $w = 5$

$H = 2$ $W = 2$

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

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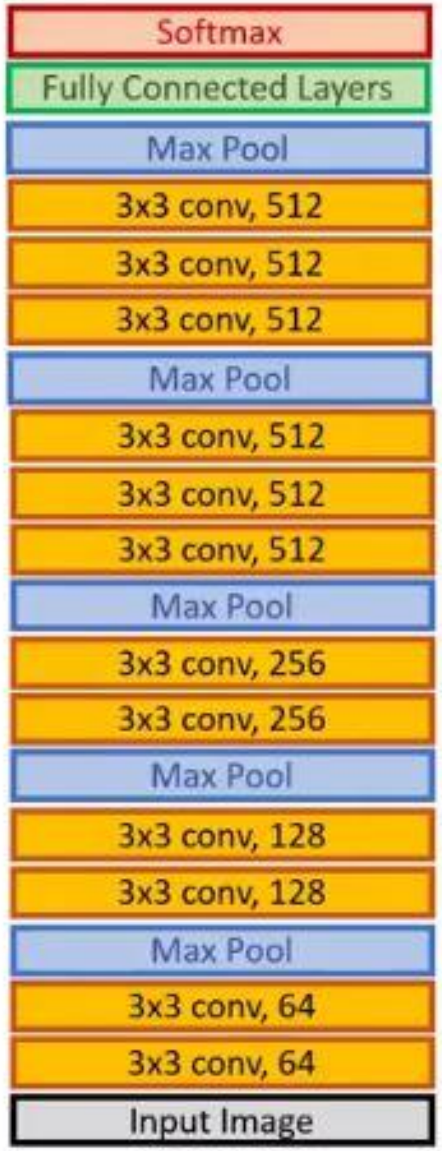
60	91
96	85

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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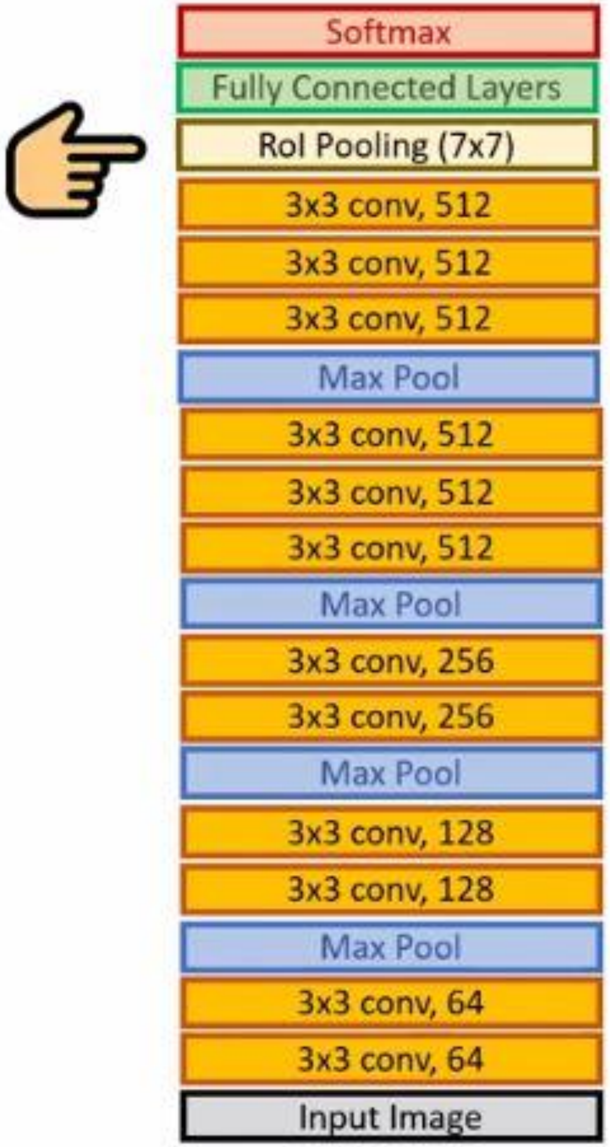

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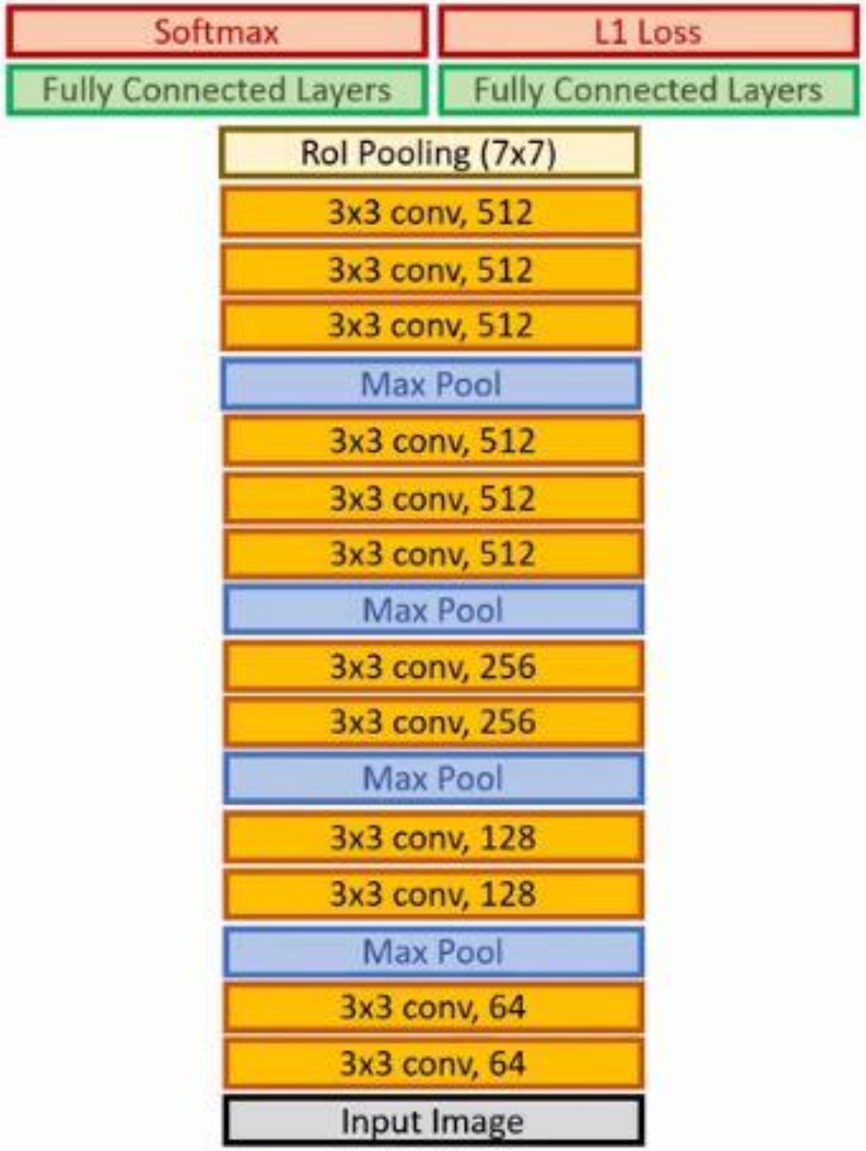

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Second, the network's last fully connected layer and softmax (which were trained for 1000-way ImageNet classification) are replaced with the two sibling layers described earlier (a fully connected layer and softmax over $K+1$ categories and category-specific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

Initializing from pre-trained networks

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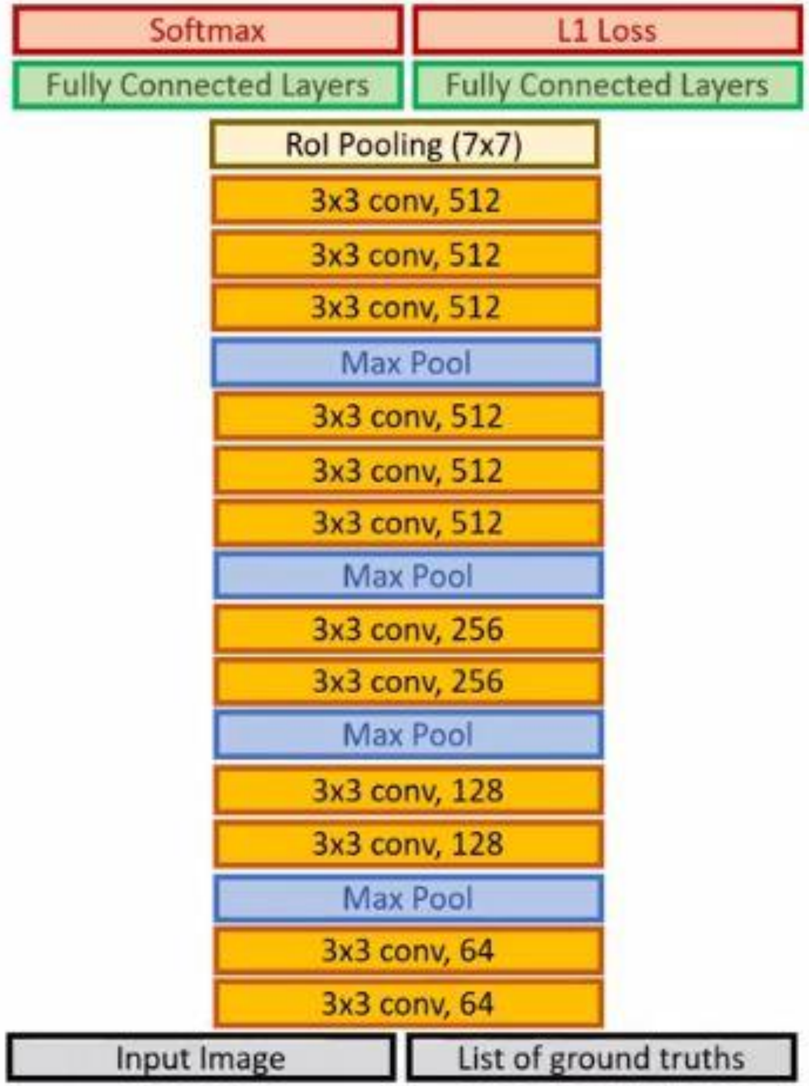

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Third, the network is modified to take two data inputs: a list of images and a list of RoIs in those images.

Fine-tuning for detection

Mini-batch sampling

Mini-batch sampling

Mini-batch sampling

Mini-batch 2

Mini-batch 3

Mini-batch 4

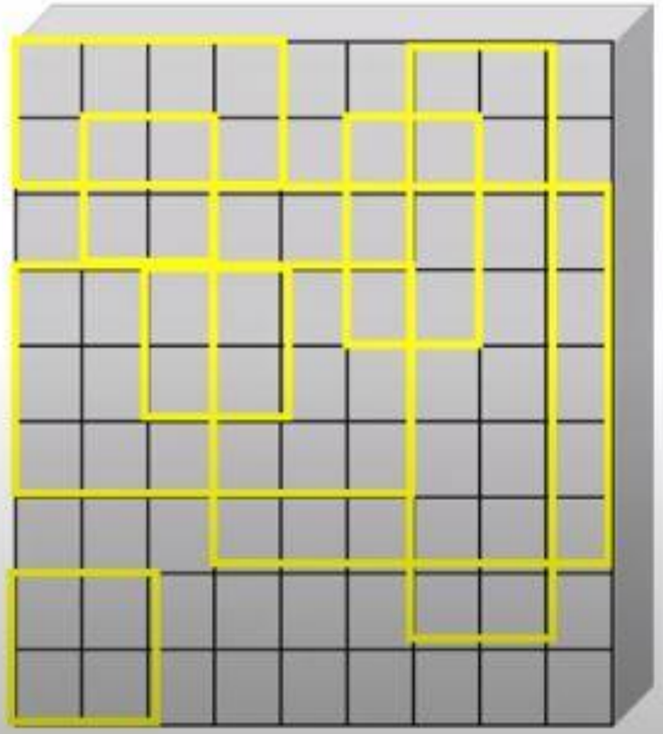
Mini-batch sampling

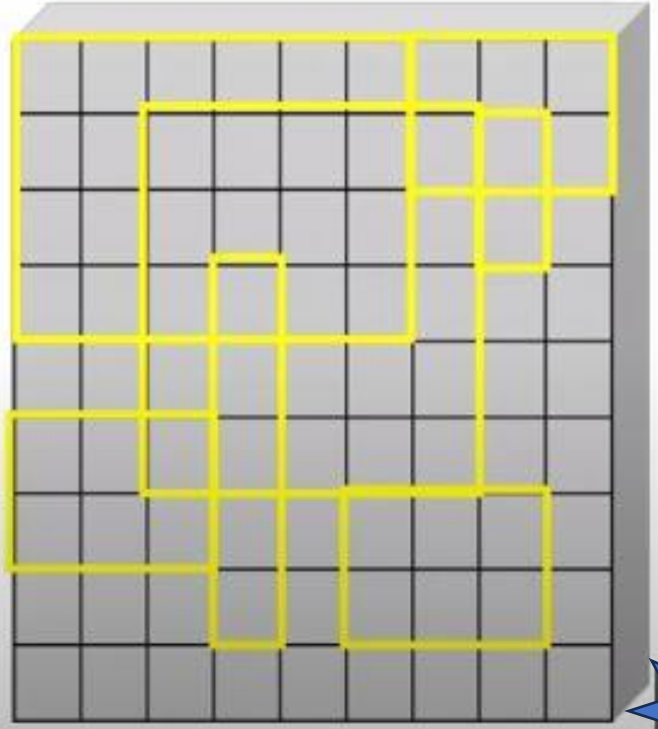
It only selects 64 RoIs from each image!

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

Object classes

Background

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:	Ground truths:
1 $p = (p_0, \ldots, p_K)$ over $\underbrace{K}_{\text{Object classes}} + \underbrace{1}_{\text{Background}}$ categories	u
2 $t^k = (t^k_x, t^k_y, t^k_w, t^k_h)$	v

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

- $L_{\text{cls}}(p, u) = -\log p_u$ $\quad \left(L_{CE} = -\sum_i \underbrace{p_i^*}_{\text{True class distribution}} \log \underbrace{p_i}_{\text{Predicted class distribution}} \right)$

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

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

  in which

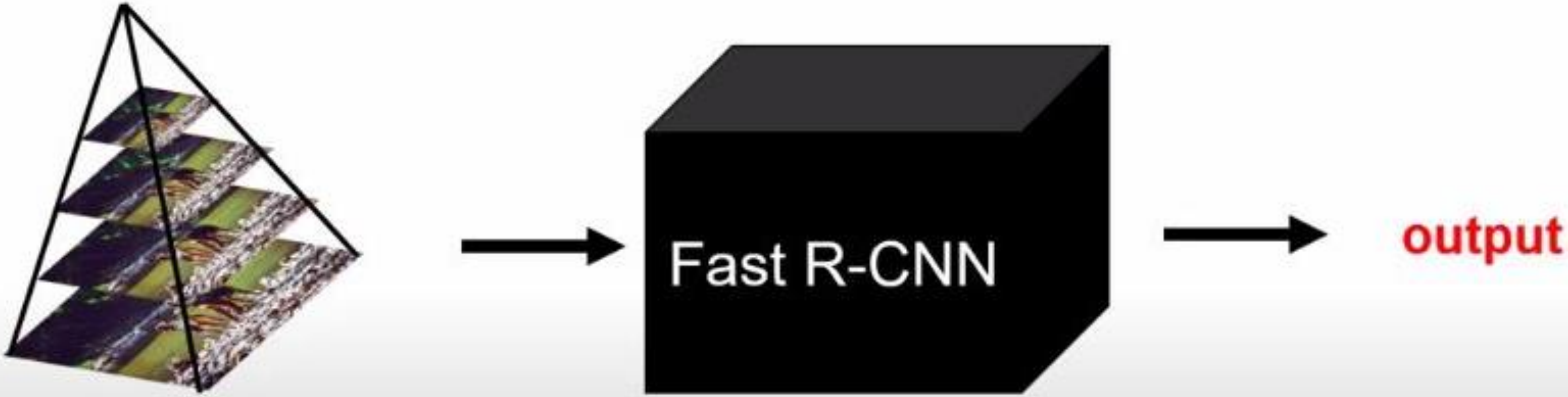
$$\text{smooth}_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise,} \end{cases}$$

Scale Invariance

Scale Invariance

Brute force

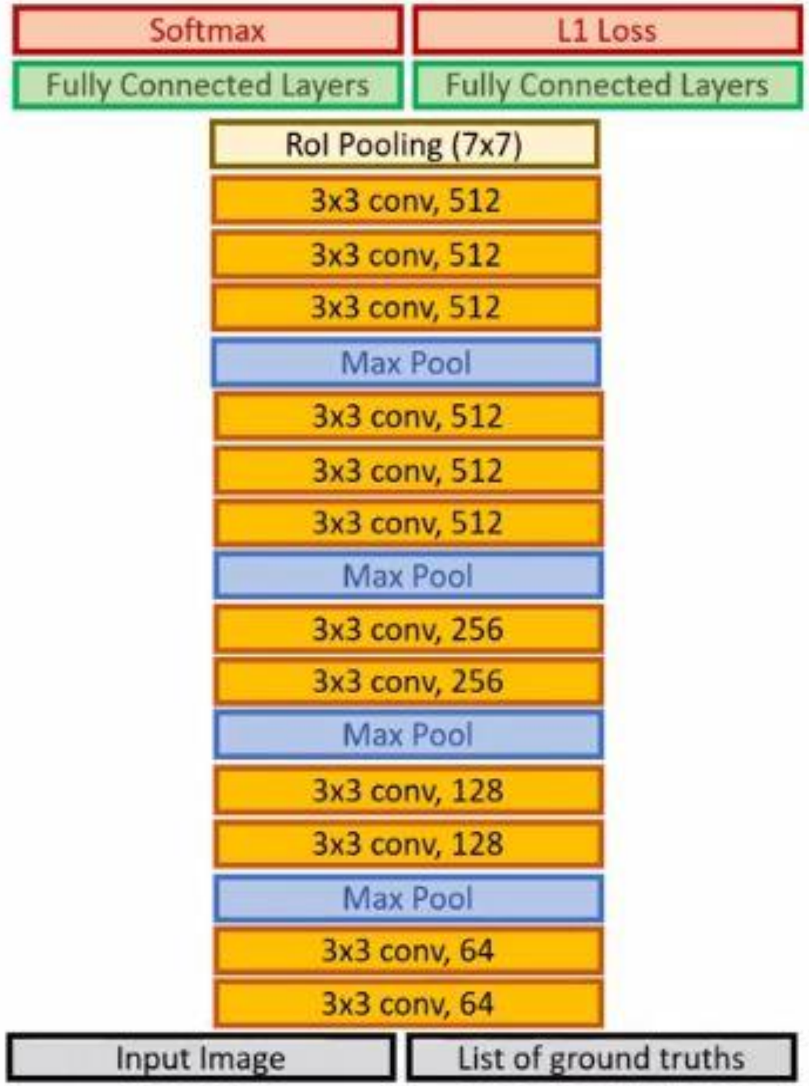
Image pyramids



- Faster RCNN

Initializing from pre-trained networks

it undergoes three transformations.



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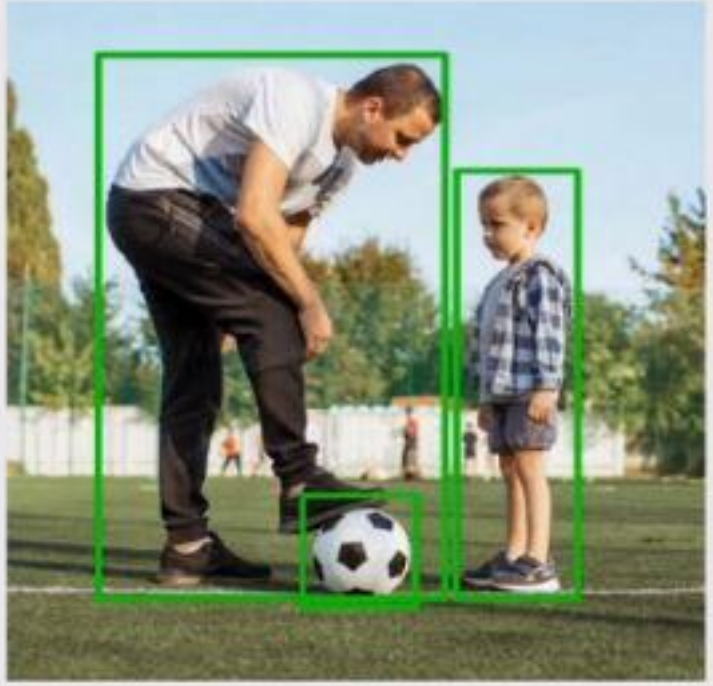
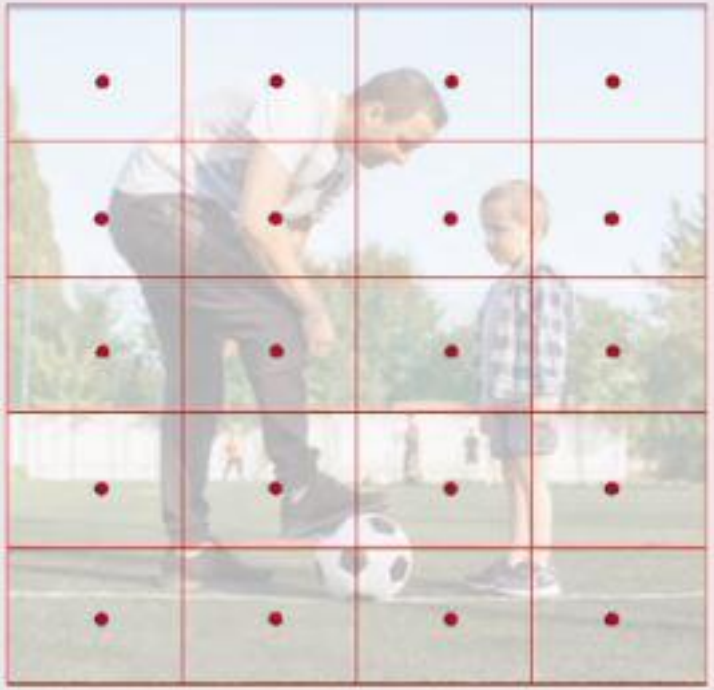
Region Proposal Network

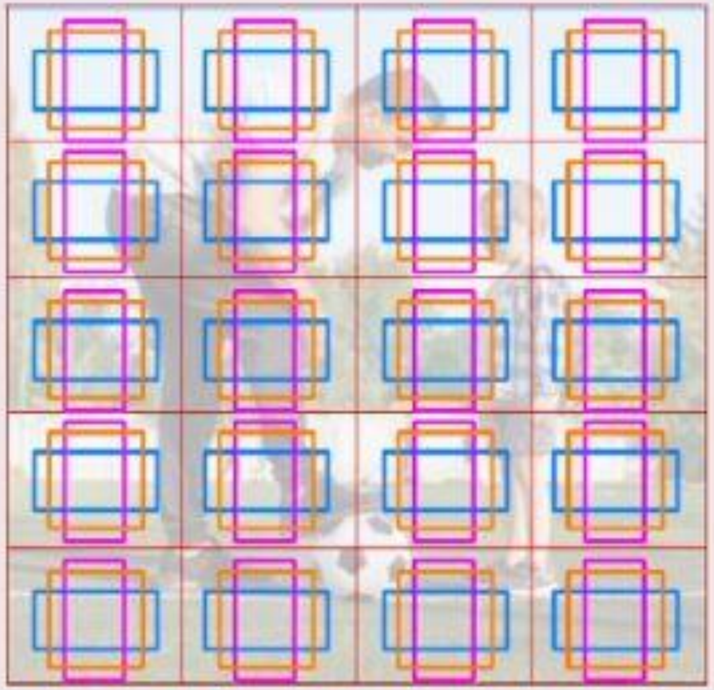
RPN



Input Image

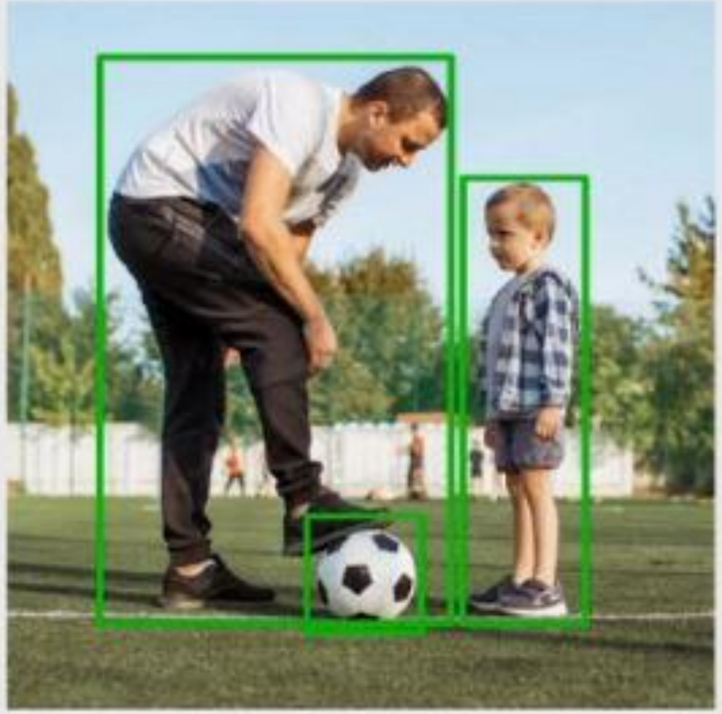


Define Anchor Points

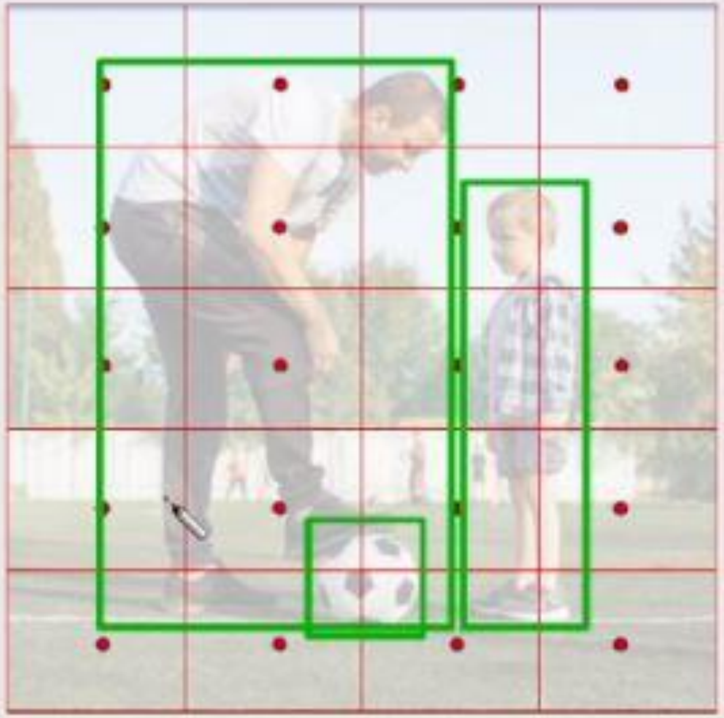


Define Anchor Boxes
(centered at Anchor Points)

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



Input Image



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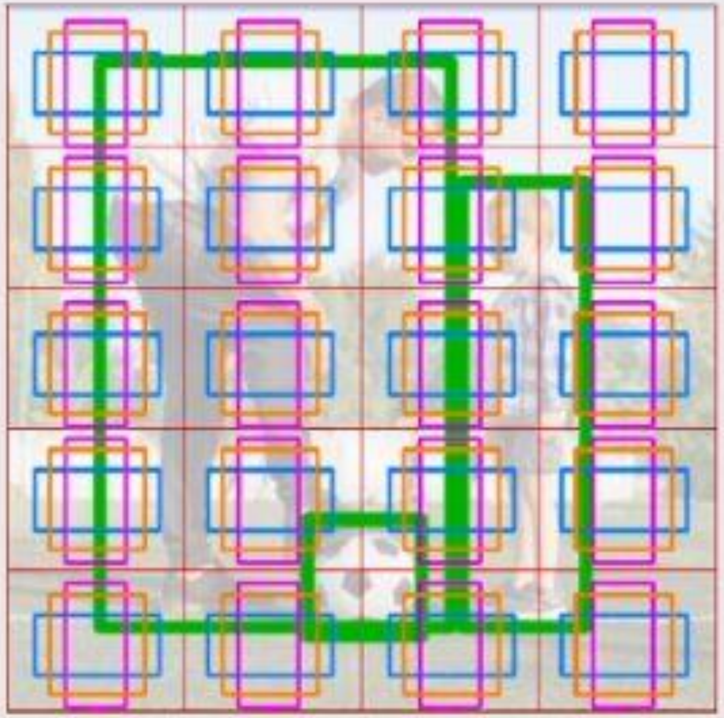
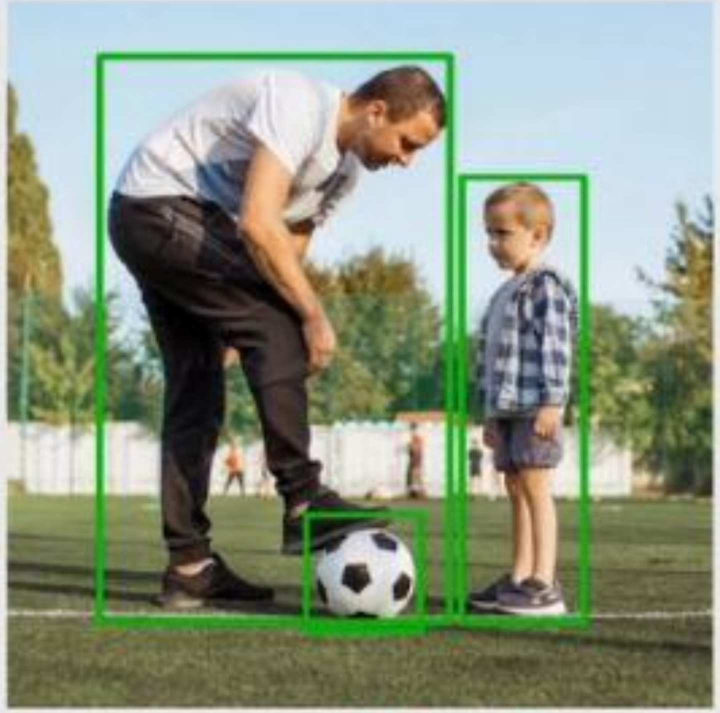
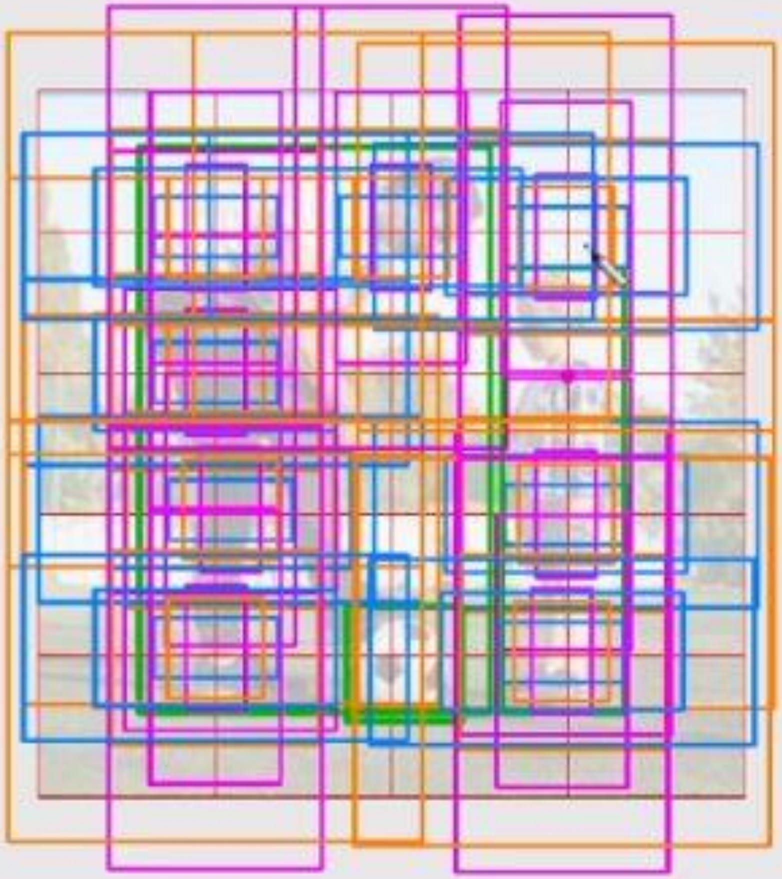


Define Anchor Boxes (centered at Anchor Points)

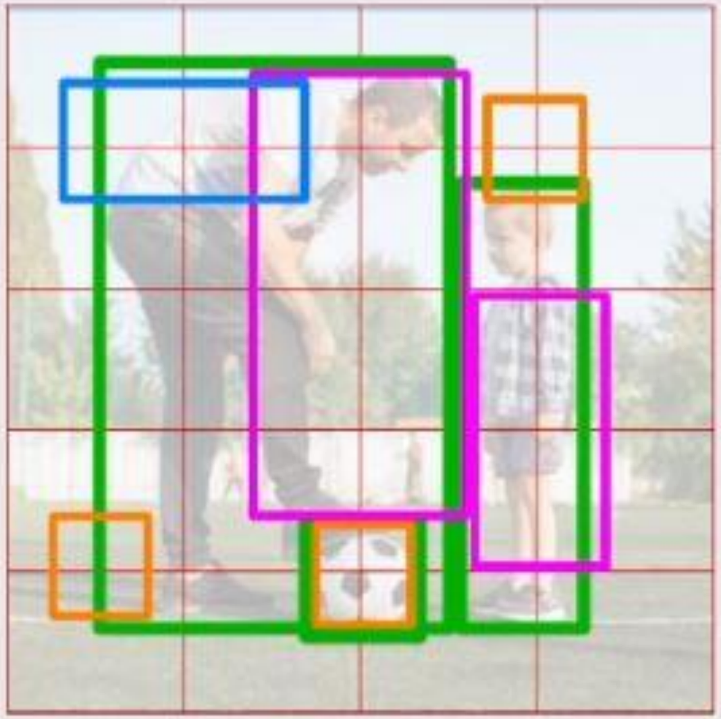
- *Selected sizes of Anchor boxes are <u>too small</u> (with respect to objects)*
- *Only Ball <u>may be</u> detected by anchor boxes*
- *Other anchor boxes will be assumed as background (IOU with ground truth is small)*



Input Image
with Ground Truth

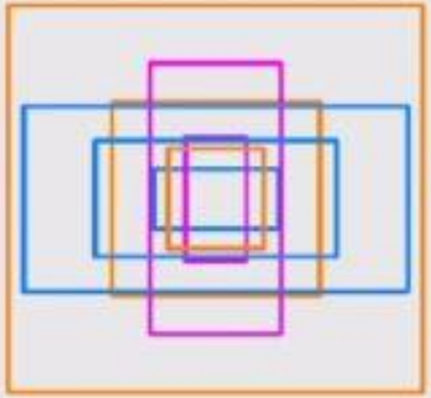


Define Anchor Points



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

Others with small IOU (**Background**)



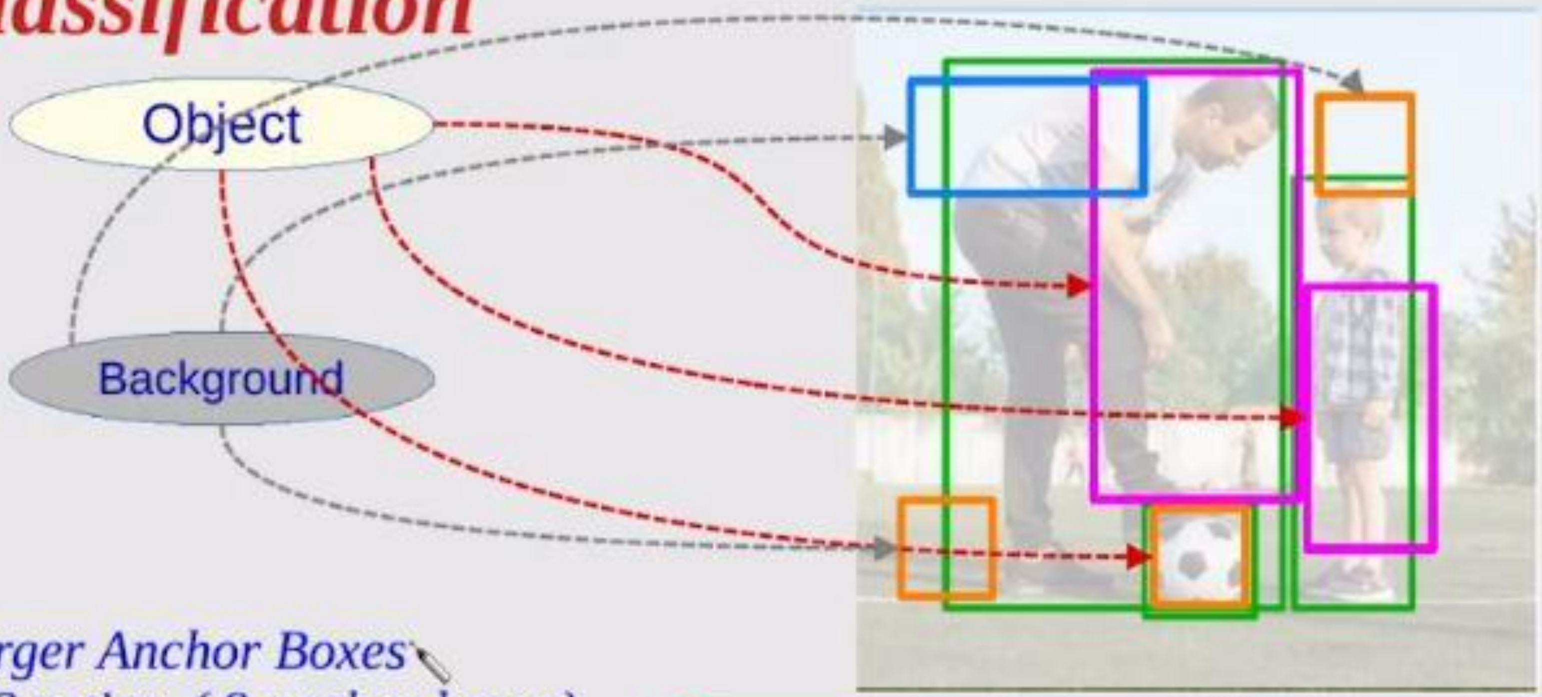
Define Larger Anchor Boxes
3 scales, 3 ratios (9 anchor boxes)

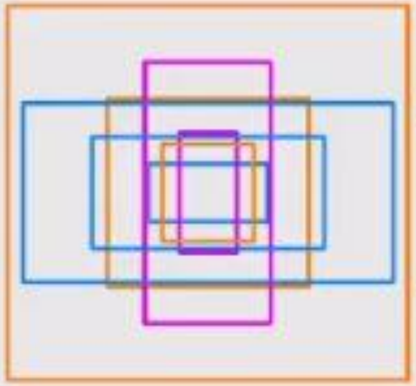
Note: Many Overlaps between boxes (No Problem)

Anchor Boxes classification

Some Anchor boxes with High IOU
(Objects)

Some Anchor Boxes with small IOU
(Background)





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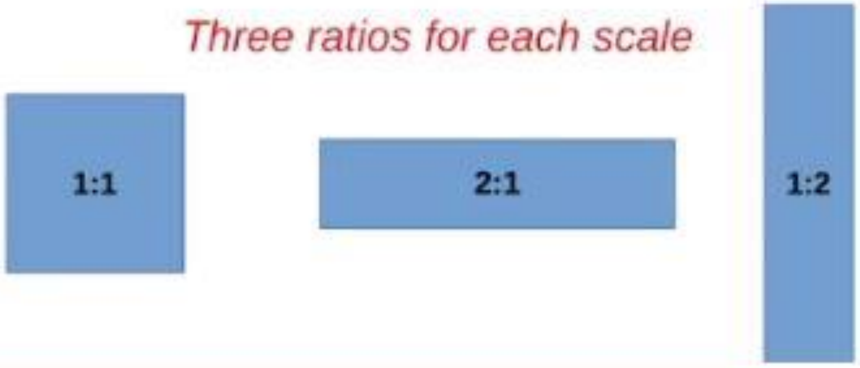
3 scales, 3 ratios (9 anchor boxes)

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

<u>**Classification**</u> (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

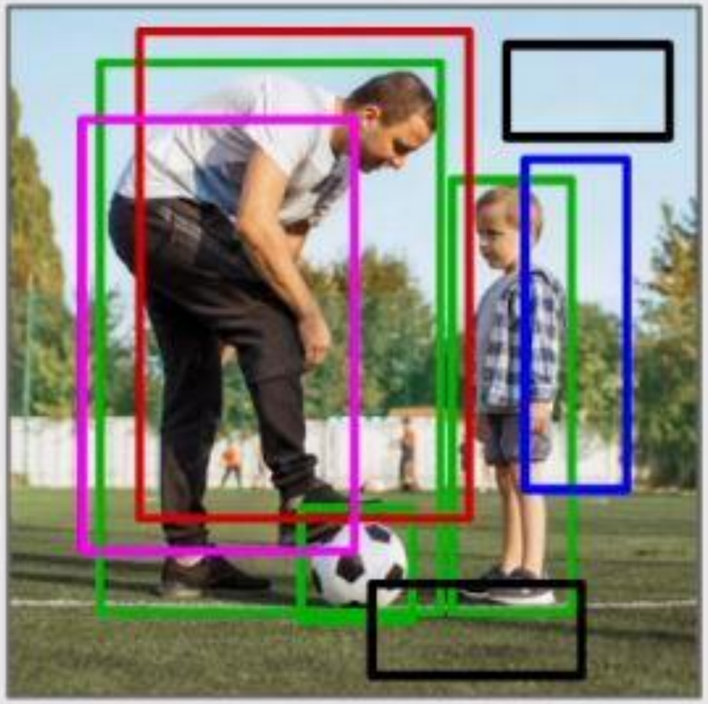
Positive

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 $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$

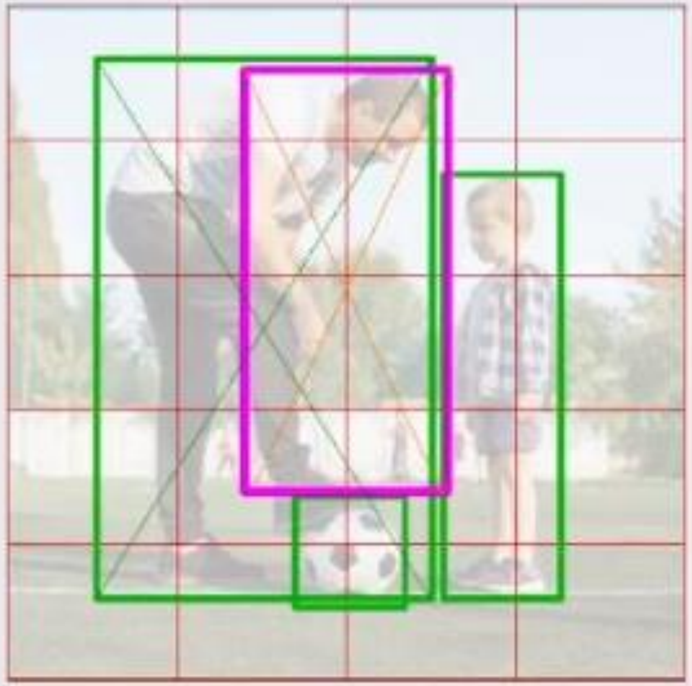


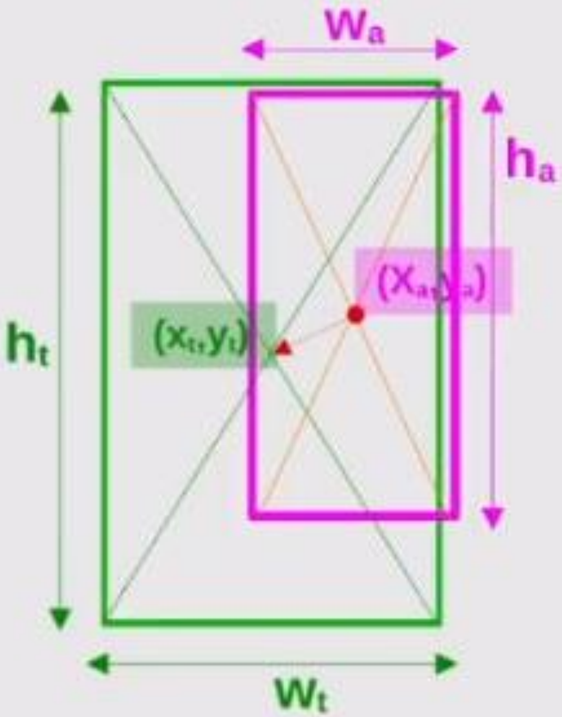
Undetermined (Mixed)

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*

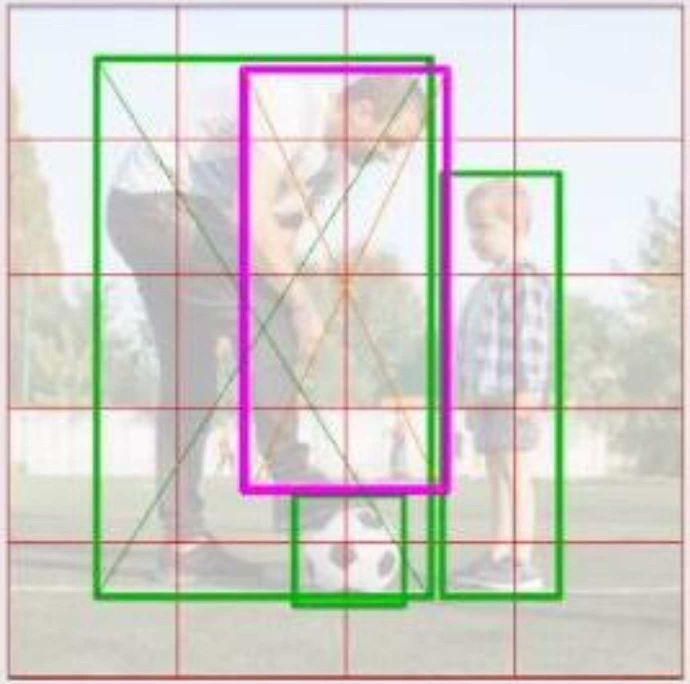
(w_t, h_t) *Width and height of Object*

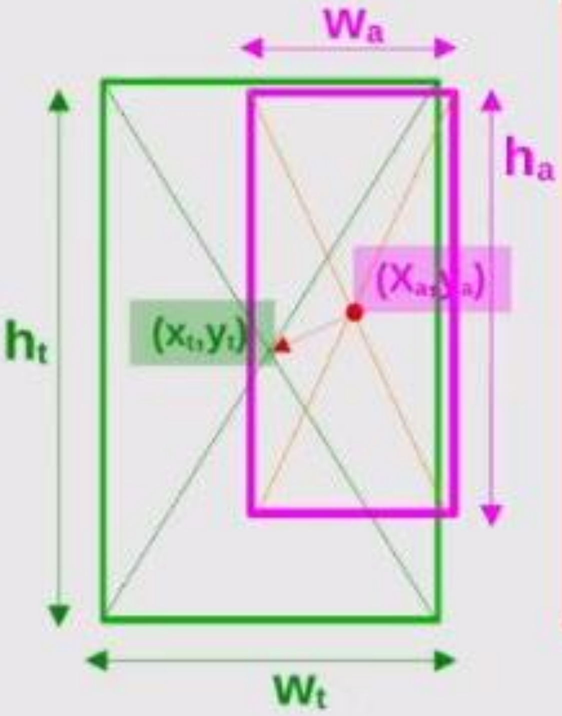
Define Anchor Box with

(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)

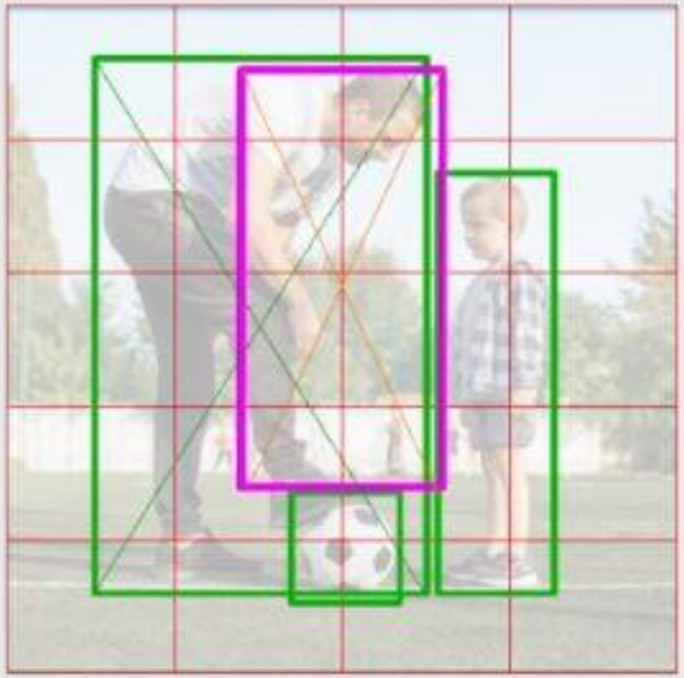
$(x_a, y_a) \rightarrow (x_t, y_t)$
***displacement** is $(x_t - x_a)$ and $(y_t - y_a)$*

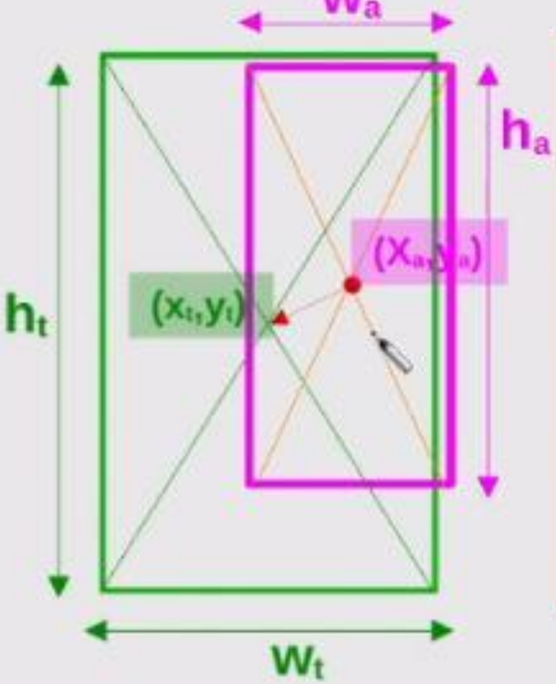
$(w_a, h_a) \rightarrow (w_t, h_t)$
***Scale difference** is w_t/w_a and h_t/h_a*

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* $(y_t - y_a)$

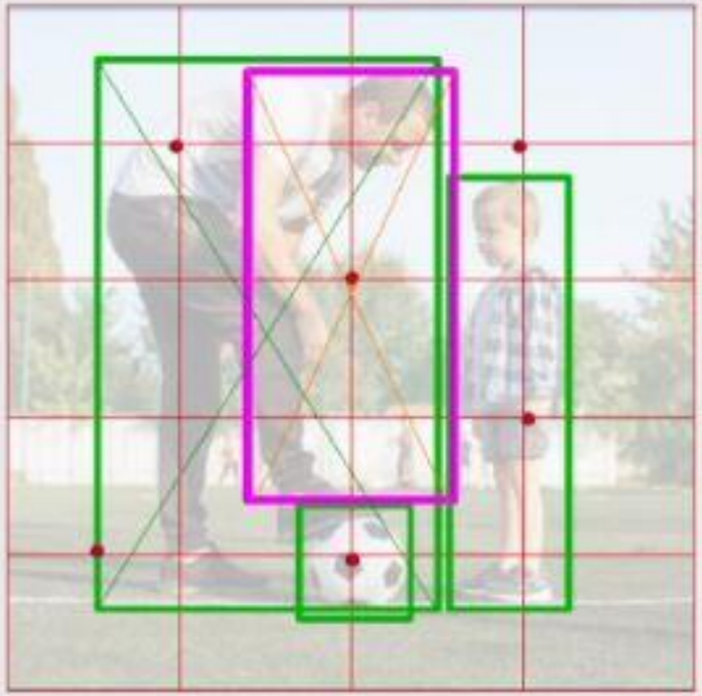
$(w_a, h_a) \rightarrow (w_t, h_t)$
Scale difference *is* w_t/w_a *and* h_t/h_a

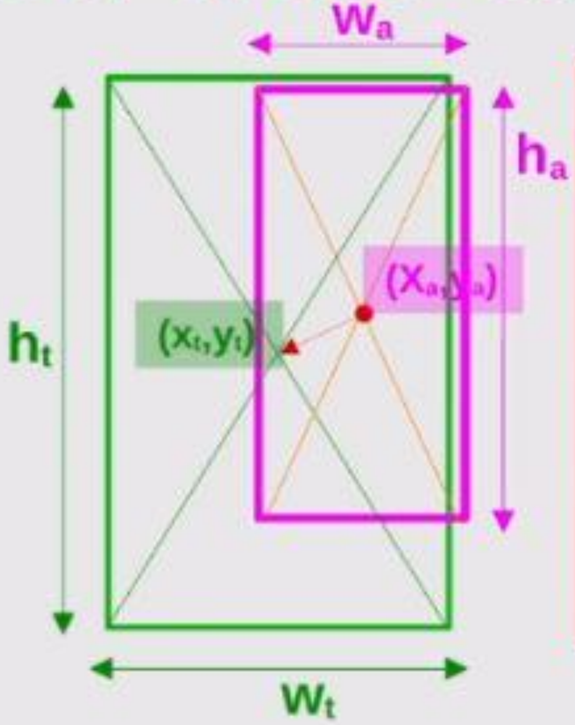
Normalize values in order to be *<u>object size independent</u>*
Use $\mathbf{d_x} = (x_t - x_a)/x_a$
$\mathbf{d_y} = (y_t - y_a)/y_a$
$\mathbf{d_w} = w_t/w_a$
$\mathbf{d_h} = h_t/h_a$

$\Rightarrow$

If Anchor Box fit 100% with Object box then
$\mathbf{d_x} = 0$
$\mathbf{d_y} = 0$
$\mathbf{d_w} = 1$ -------??
$\mathbf{d_h} = 1$ ------ ??

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

$\Rightarrow$

If Anchor Box fit 100% with Object box then

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

Use Log function

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

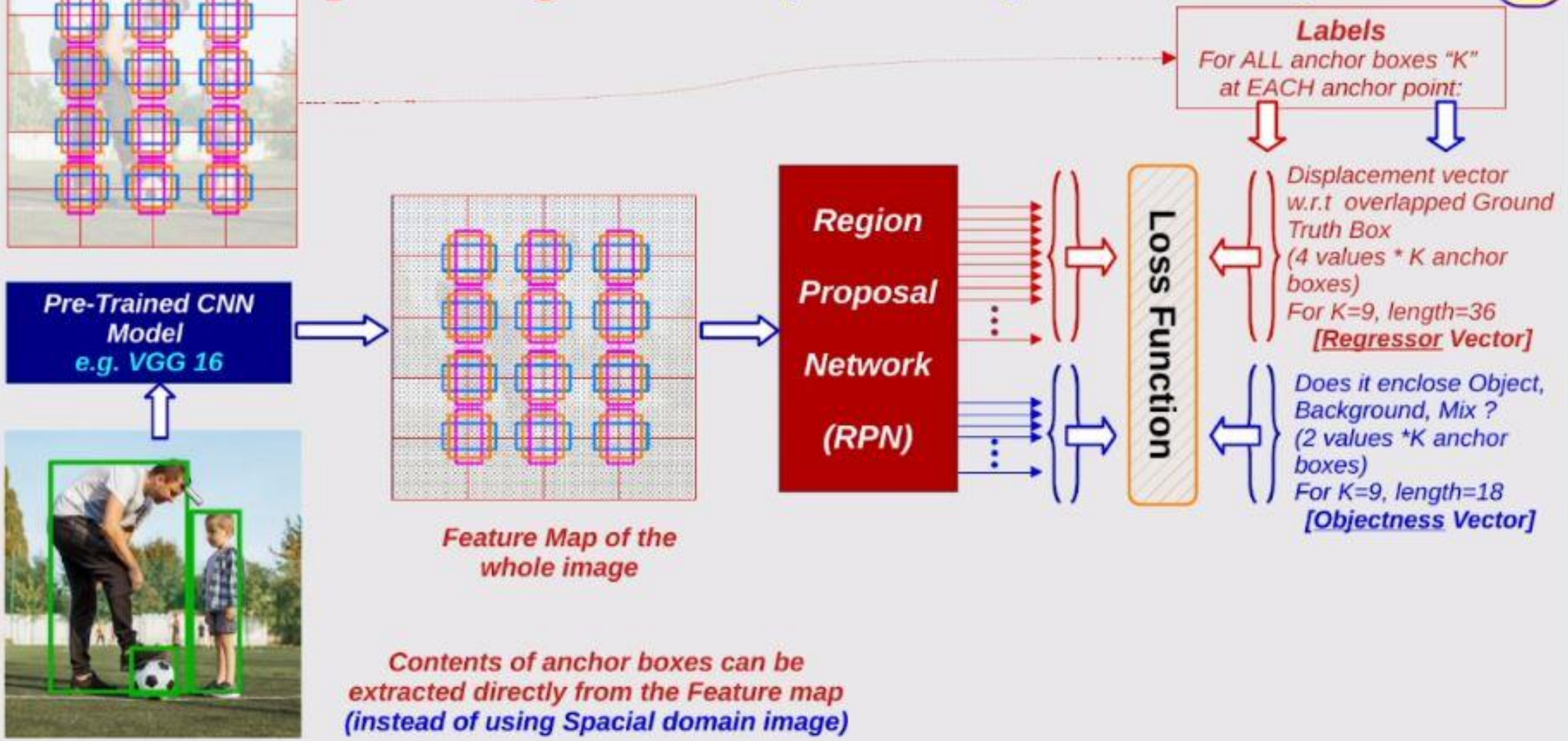
If Anchor Box fit 100% with Object box then

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

All Values are <u>zeros</u>

[3] RPN Training Data Preparation

[Training of RPN *(The Complete Picture)*



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.