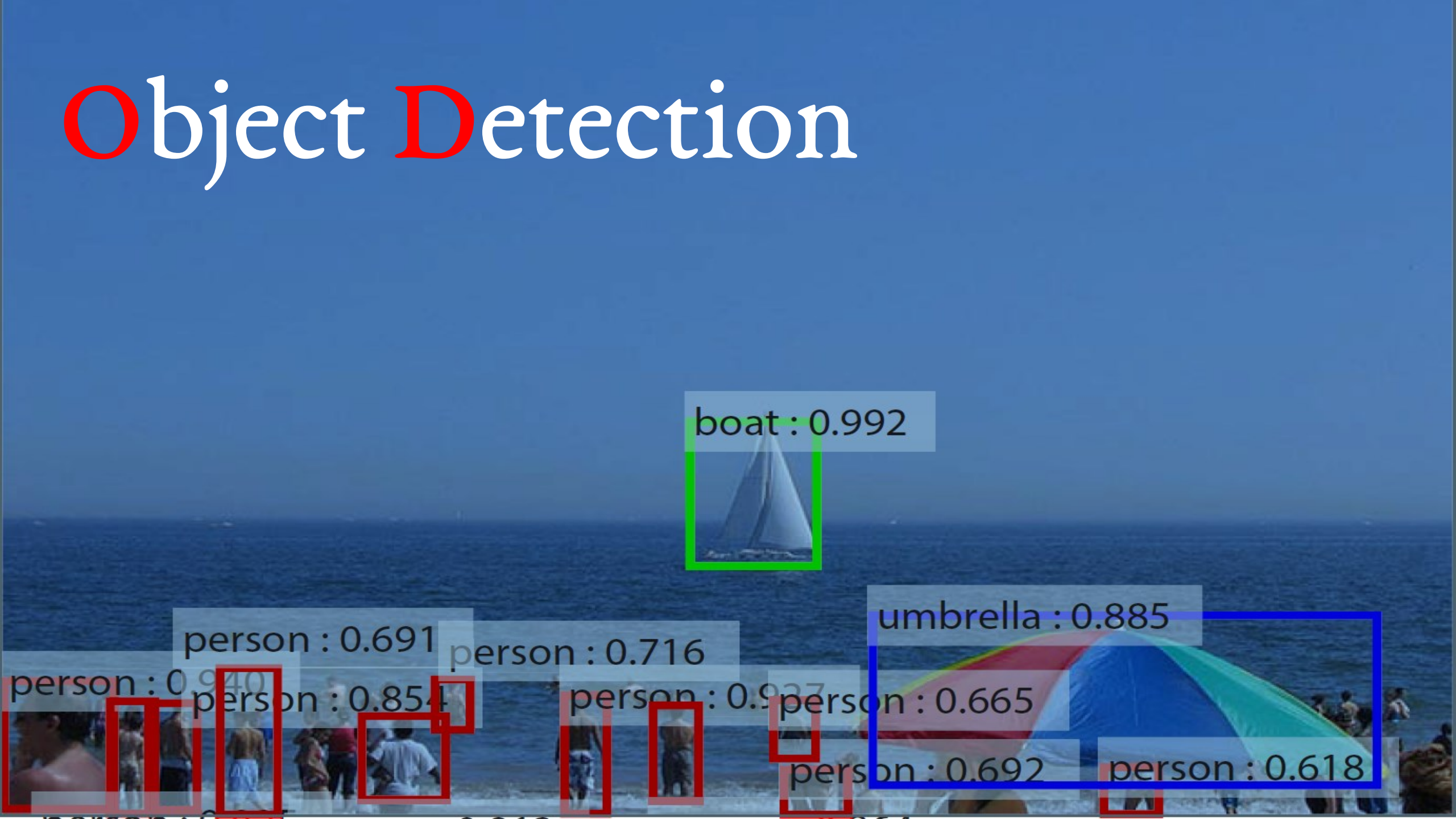
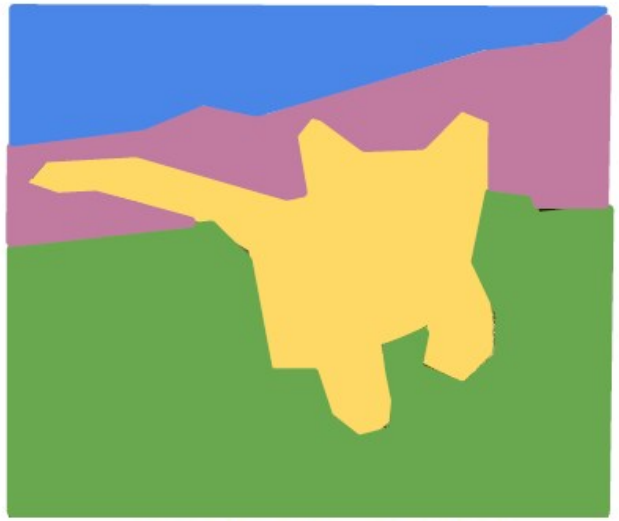
Object Detection



Computer Vision Task

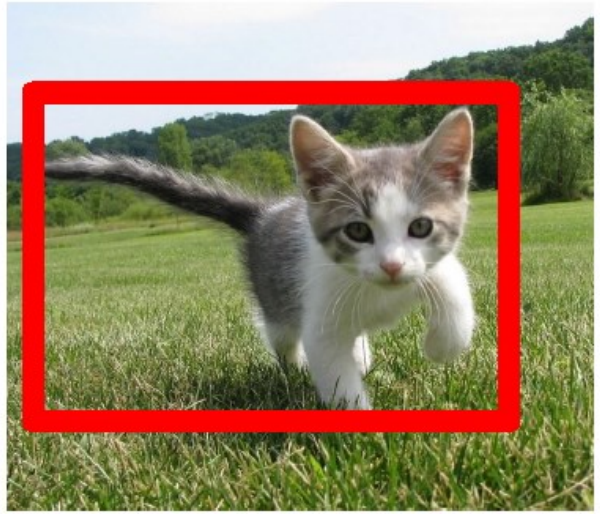
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

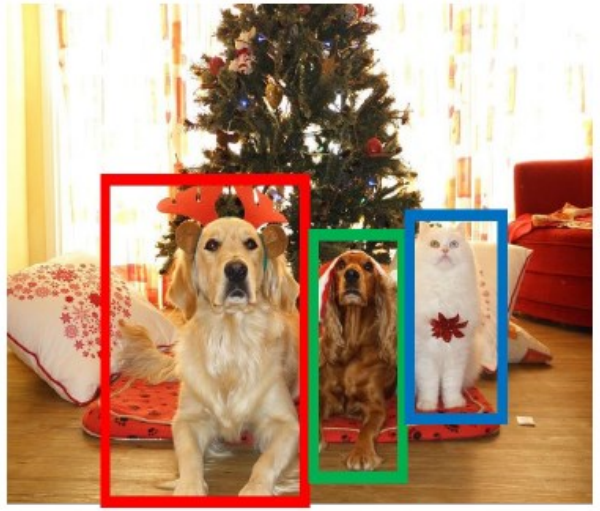
Classification + Localization



CAT

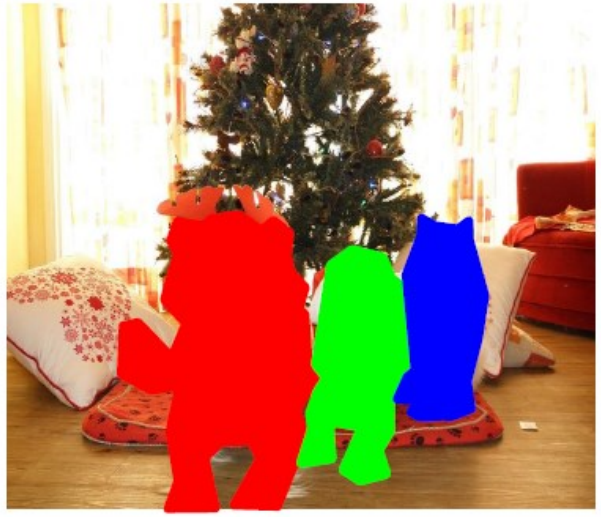
Single Object

Object Detection



DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

Multiple Object

Classification + Localization

Classification: C classes
Input: Image
Output: Class label
Evaluation metric: Accuracy

→ CAT

Localization:
Input: Image
Output: Box in the image (x, y, w, h)
Evaluation metric: Intersection over Union

→ (x, y, w, h)

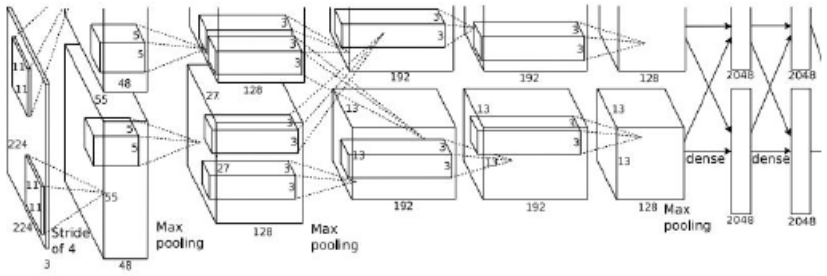
Classification + Localization: Do both

Intersection Over Union

$$\text{Jaccard Overlap} = \text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

Classification + Localization

This image is CC0 public domain



Correct label:
Cat

Fully Connected:
4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Softmax Loss

Multitask Loss

Loss

Vector:
4096

Fully Connected:
4096 to 4

Box Coordinates
(x, y, w, h)

L2 Loss

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

Treat localization as a regression problem!

Detection as Regression?

CAT, (x, y, w, h)
CAT, (x, y, w, h)
....
CAT (x, y, w, h)

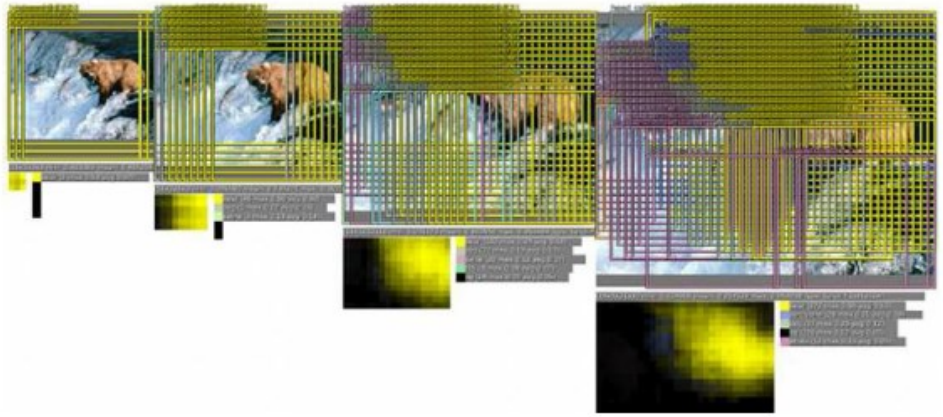
= many numbers

Need variable sized outputs

How to Find BBox

- Intuitive Approach – Sliding window
  - Simple but takes a lot of time
  - Multi-scale testing is necessary

  - Procedure
    - ➢ Perform classification at each location
    - ➢ Perform bounding-box regression on all the classified regions
    - ➢ Merge bounding boxes



R-CNN

1. Generating category independent region proposals
2. Extracting a fixed length feature vector from CNN
3. Class specific linear SVM

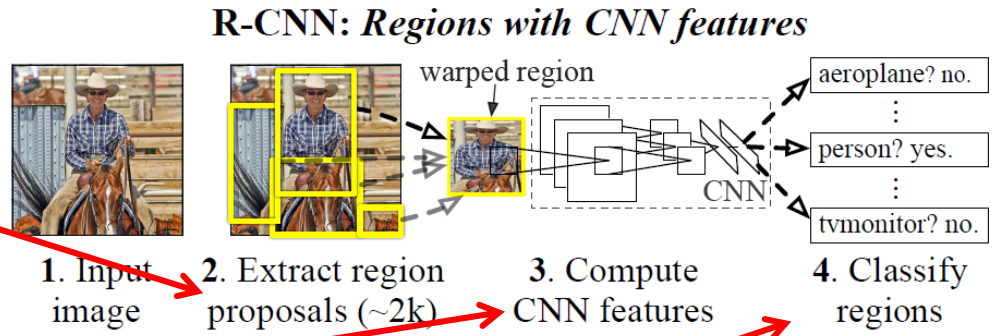
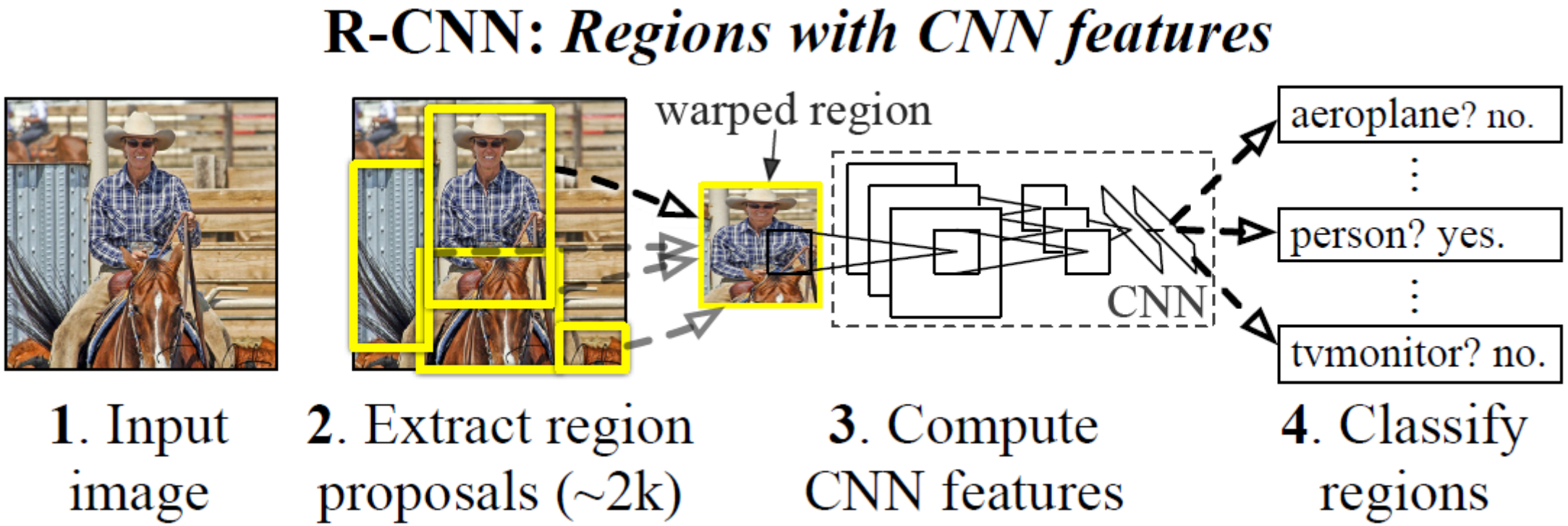
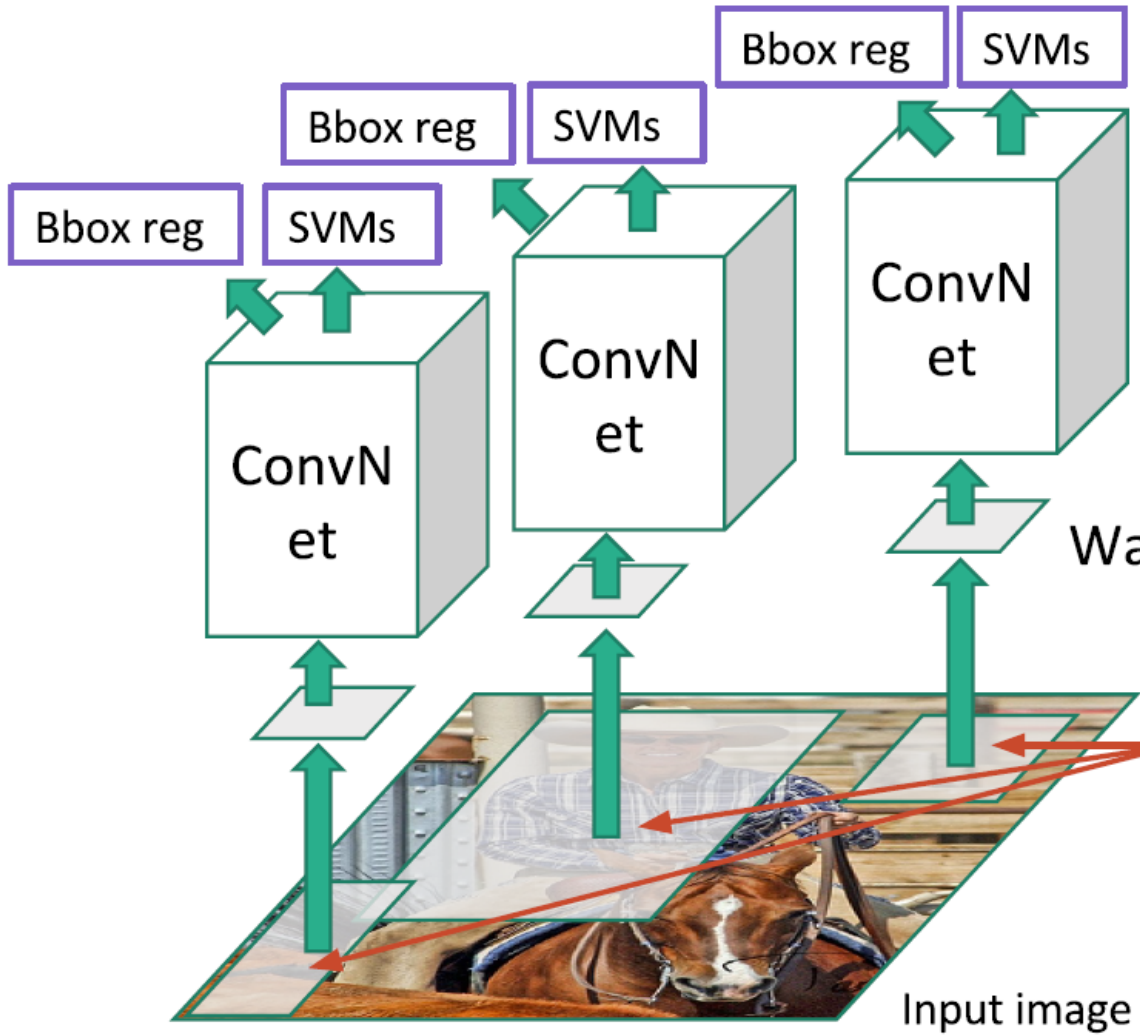


Figure 1: Object detection system overview. Our system (1) takes an input image, (2) extracts around 2000 bottom-up region proposals, (3) computes features for each proposal using a large convolutional neural network (CNN), and then (4) classifies each region using class-specific linear SVMs. R-CNN achieves a mean average precision (mAP) of **53.7% on PASCAL VOC 2010**. For comparison, [39] reports 35.1% mAP using the same region proposals, but with a spatial pyramid and bag-of-visual-words approach. The popular deformable part models perform at 33.4%. On the 200-class **ILSVRC2013 detection dataset, R-CNN's mAP is 31.4%**, a large improvement over OverFeat [34], which had the previous best result at 24.3%.

R-CNN Architecture



R-CNN



Linear Regression for bounding box offsets

Classify regions with SVMs

Forward each region through ConvNet

Warped image regions

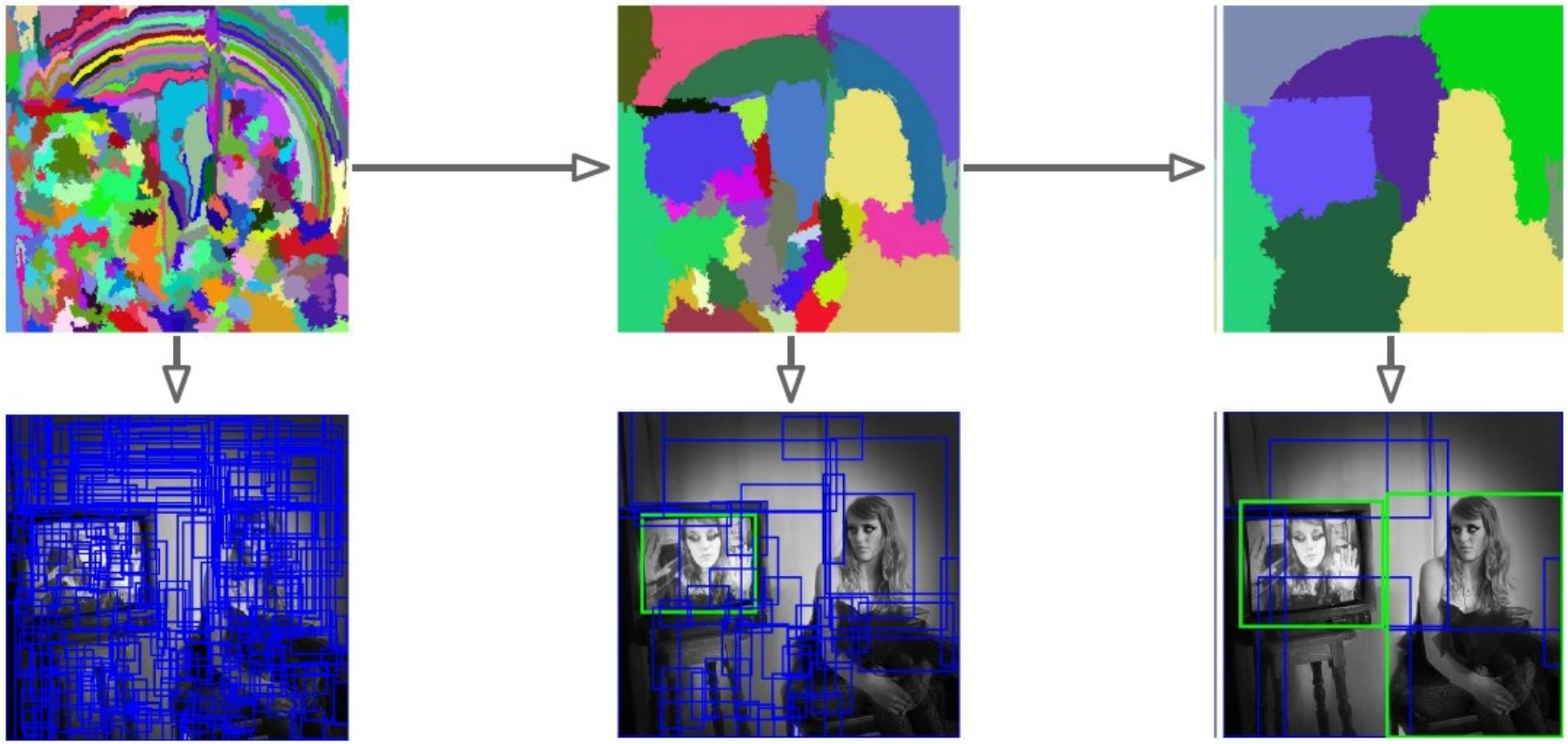
Regions of Interest (RoI) from a proposal method (~2k)

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

Region Proposals – Selective Search

- Bottom-up segmentation, merging regions at multiple scales

Convert regions to boxes



Feature Extraction

- AlexNet is used

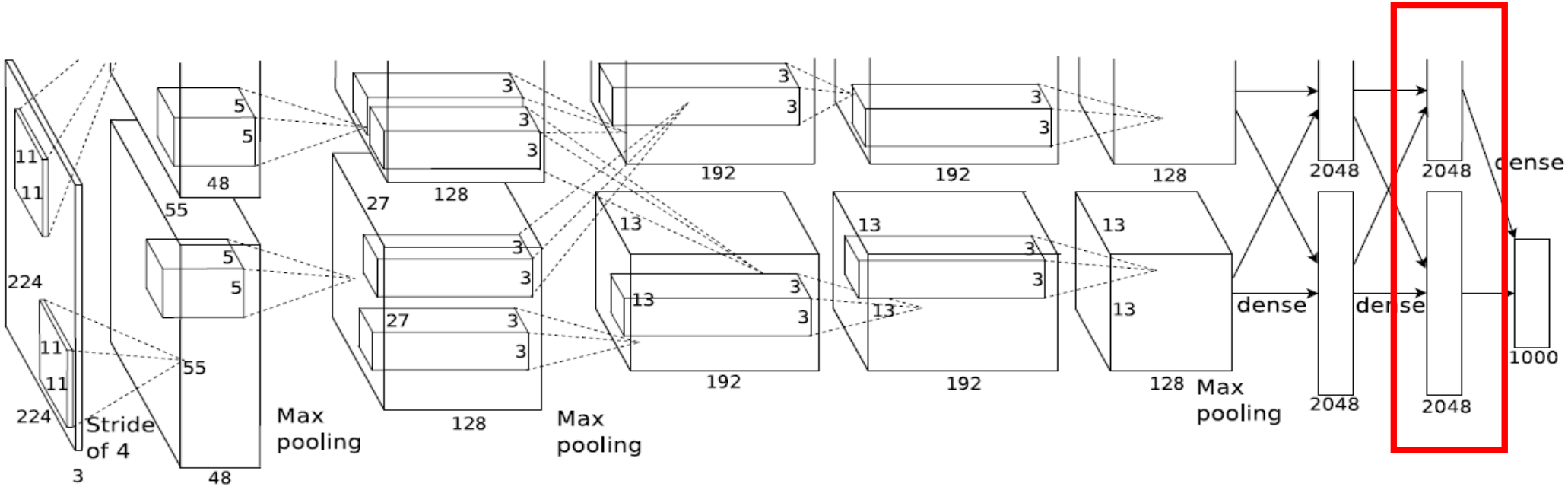
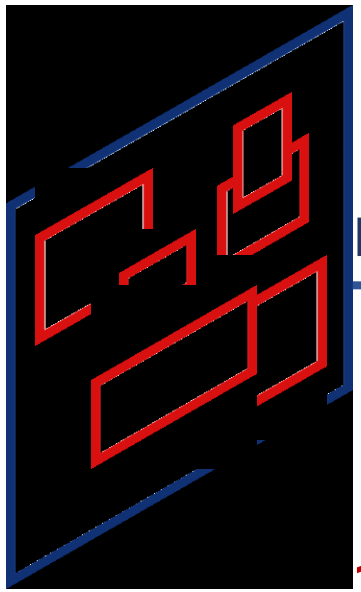


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

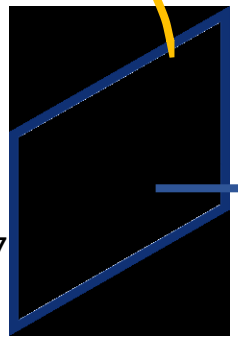
Test Time

2,000 region proposals are extracted

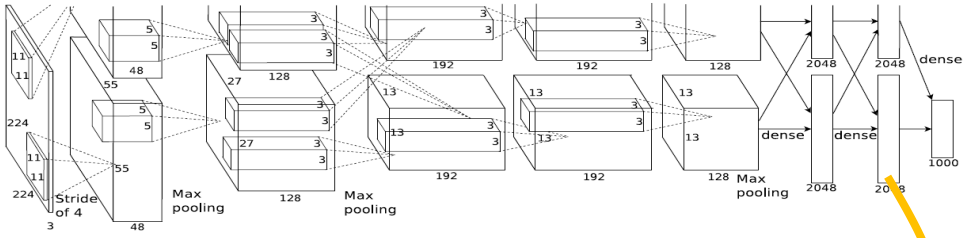


Reshape(warping)

227



CNN



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4096

SVM

20+1

13s/image on a GPU

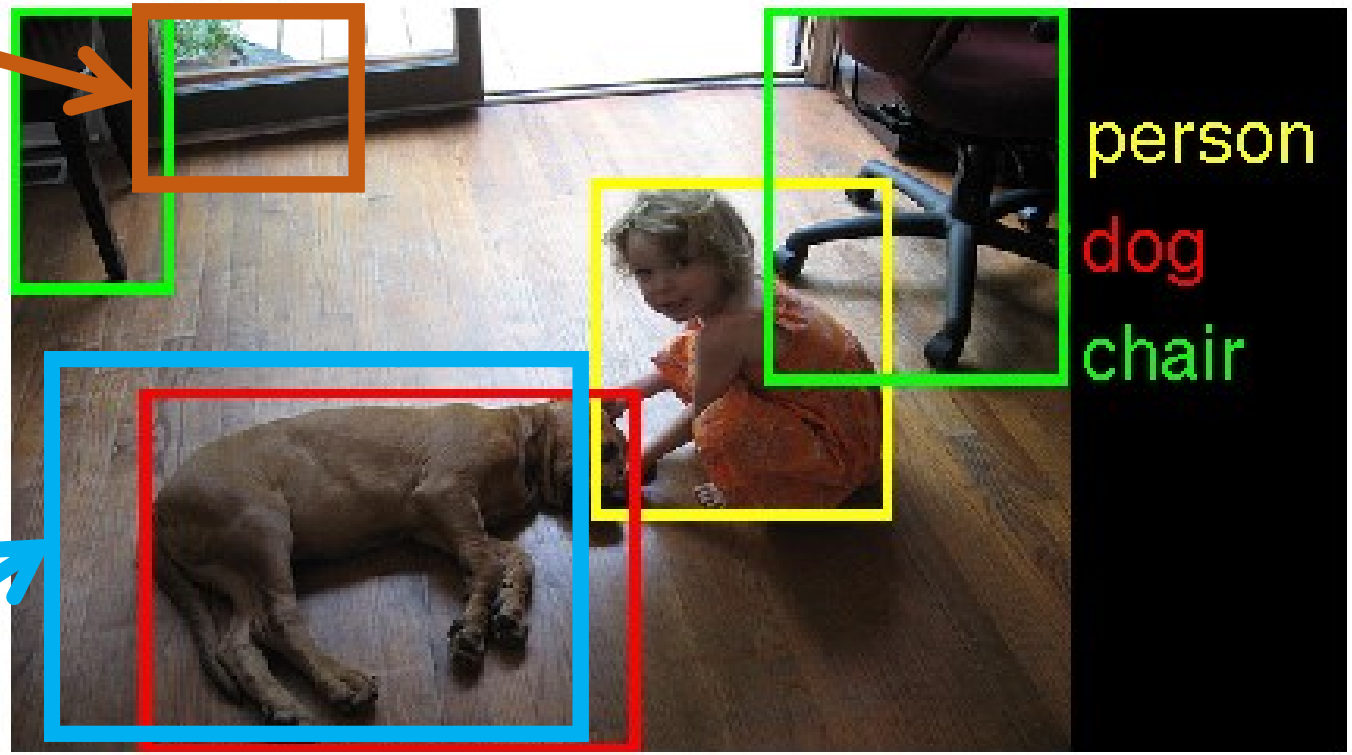
53s/image on a CPU

Training(Region Proposal)

Positive : groundtruth

Negative (BG) : if IoU ≤ 0.3

Training SVM



Fine-tuning

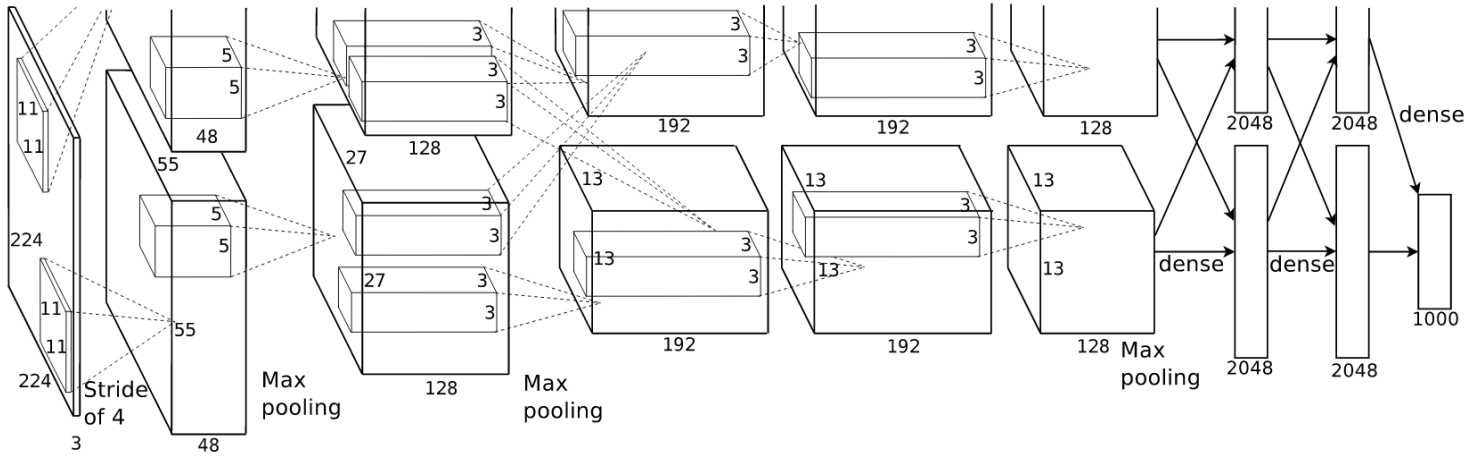
Positive (FG) : if IoU ≥ 0.5

Negative (BG) : else

R-CNN Training

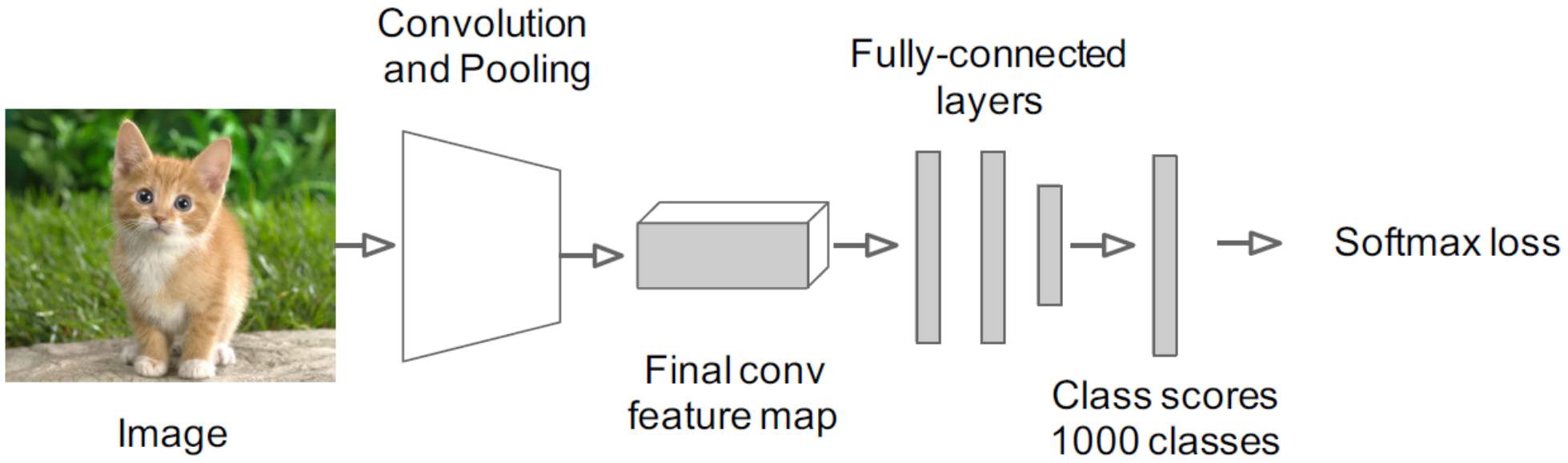
"Post hoc" means the parameters are learned after the ConvNet is fixed

- Pre-train a ConvNet(AlexNet) for ImageNet classification dataset
- Fine-tune for object detection(softmax + log loss)
- Cache feature vectors to disk
- Train post hoc linear SVMs(hinge loss)
- Train post hoc linear bounding-box regressors(squared loss)



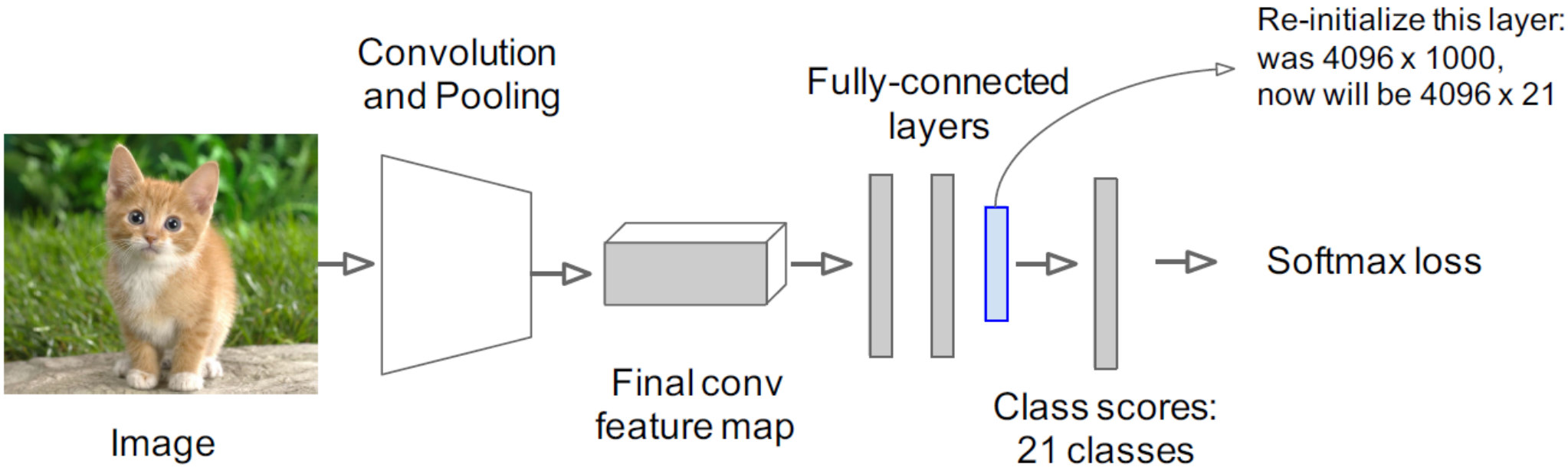
Training

- Step 1: Train (or download) a classification model for ImageNet (AlexNet)



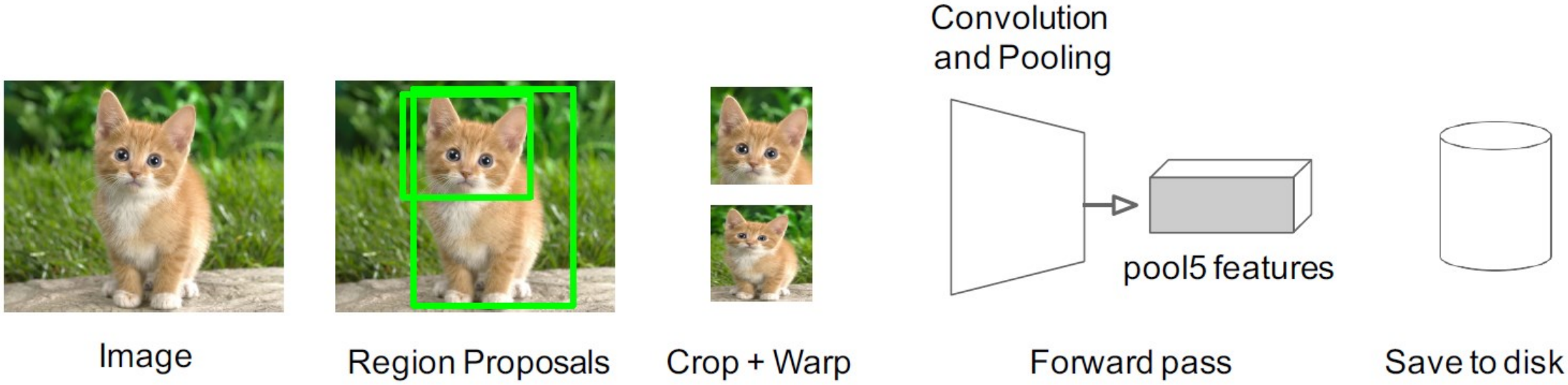
Training

- Step 2: Fine-tune model for detection
  - Instead of 1000 ImageNet classes, want 20 object classes + background
  - Throw away final fully-connected layer, reinitialize from scratch
  - Keep training model using positive / negative regions from detection images



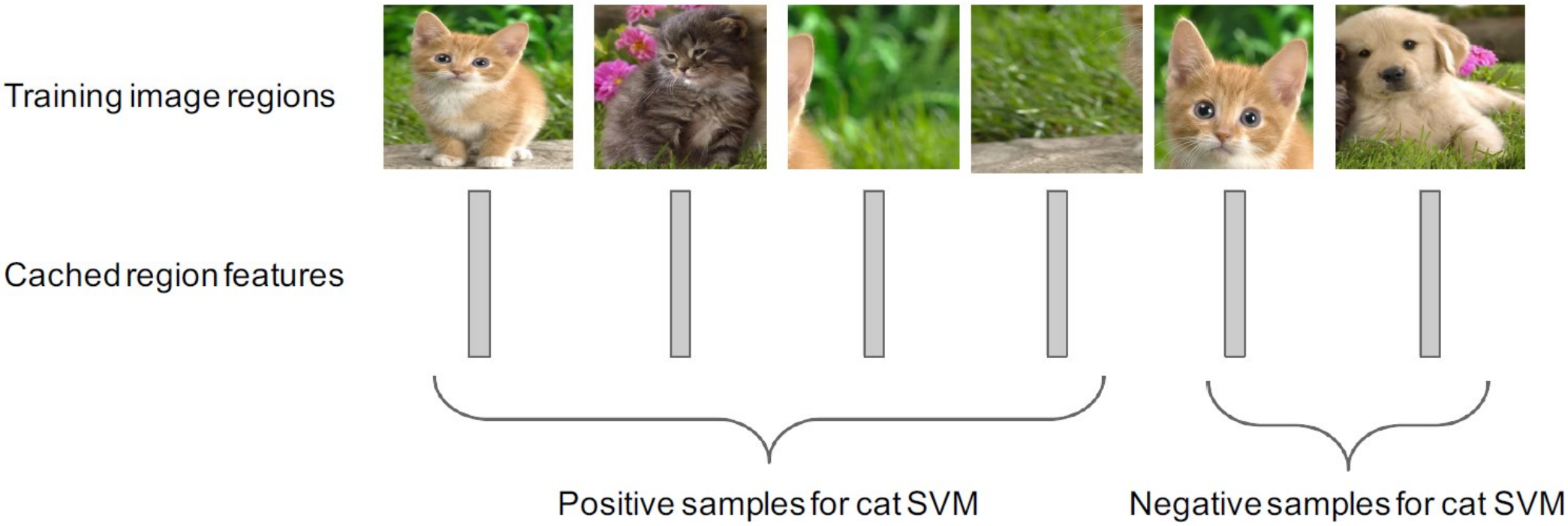
Training

- Step 3: Extract features
  - Extract region proposals for all images
  - For each region: warp to CNN input size, run forward through CNN, save pool5 features to disk
  - Have a big hard drive: features are ~200GB for PASCAL dataset!



Training

- Step 4: Train one binary SVM per class to classify region features



Training

- Step 5 (bbox regression): For each class, train a linear regression model to map from cached features to offsets to GT boxes to make up for "slightly wrong" proposals

Bounding-Box Regression

$P^i = (P^i_x, P^i_y, P^i_w, P^i_h)$ specifies the pixel coordinates of the center of proposal P^i's bounding box together with P^i's width and height in pixels

$G = (G_x, G_y, G_w, G_h)$ means the ground-truth bounding box

$$\hat{G}_x = P_w d_x(P) + P_x \quad (1)$$

$$\hat{G}_y = P_h d_y(P) + P_y \quad (2)$$

$$\hat{G}_w = P_w \exp(d_w(P)) \quad (3)$$

$$\hat{G}_h = P_h \exp(d_h(P)). \quad (4)$$

Bounding-Box Regression

Each function $d_\star(P)$ (where $\star$ is one of x, y, h, w) is modeled as a linear function of the pool_5 features of proposal P, denoted by $\phi_5(P)$. (The dependence of $\phi_5(P)$ on the image data is implicitly assumed.) Thus we have $d_\star(P) = \mathbf{w}_\star^{\mathrm{T}} \phi_5(P)$, where $\mathbf{w}_\star$ is a vector of learnable model parameters. We learn $\mathbf{w}_\star$ by optimizing the regularized least squares objective (ridge regression):

$$\mathbf{w}_\star = \underset{\hat{\mathbf{w}}_\star}{\operatorname{argmin}} \sum_i^N (t_\star^i - \hat{\mathbf{w}}_\star^{\mathrm{T}} \phi_5(P^i))^2 + \lambda \left\| \hat{\mathbf{w}}_\star \right\|^2 . \quad (5)$$

$$\hat{G}_x = P_w d_x(P) + P_x \quad (1)$$

$$\hat{G}_y = P_h d_y(P) + P_y \quad (2)$$

$$\hat{G}_w = P_w \exp(d_w(P)) \quad (3)$$

$$\hat{G}_h = P_h \exp(d_h(P)). \quad (4)$$

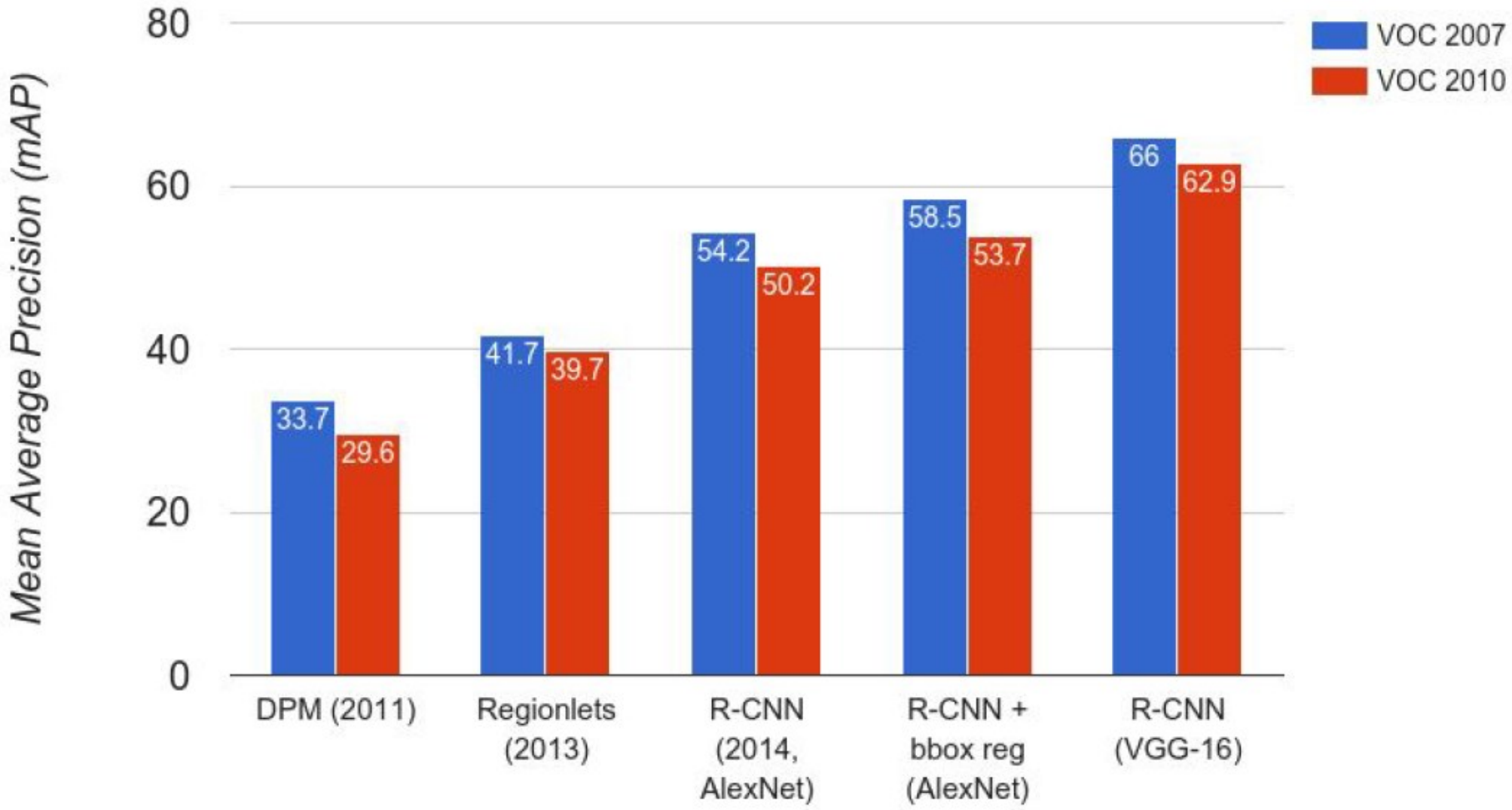
$$t_x = (G_x - P_x)/P_w \quad (6)$$

$$t_y = (G_y - P_y)/P_h \quad (7)$$

$$t_w = \log(G_w/P_w) \quad (8)$$

$$t_h = \log(G_h/P_h). \quad (9)$$

Results


Mean Average Precision (mAP)
80
60
40
20
0
VOC 2007
VOC 2010
33.7
29.6
41.7
39.7
54.2
50.2
58.5
53.7
66
62.9
DPM (2011)
Regionlets (2013)
R-CNN (2014, AlexNet)
R-CNN + bbox reg (AlexNet)
R-CNN (VGG-16)

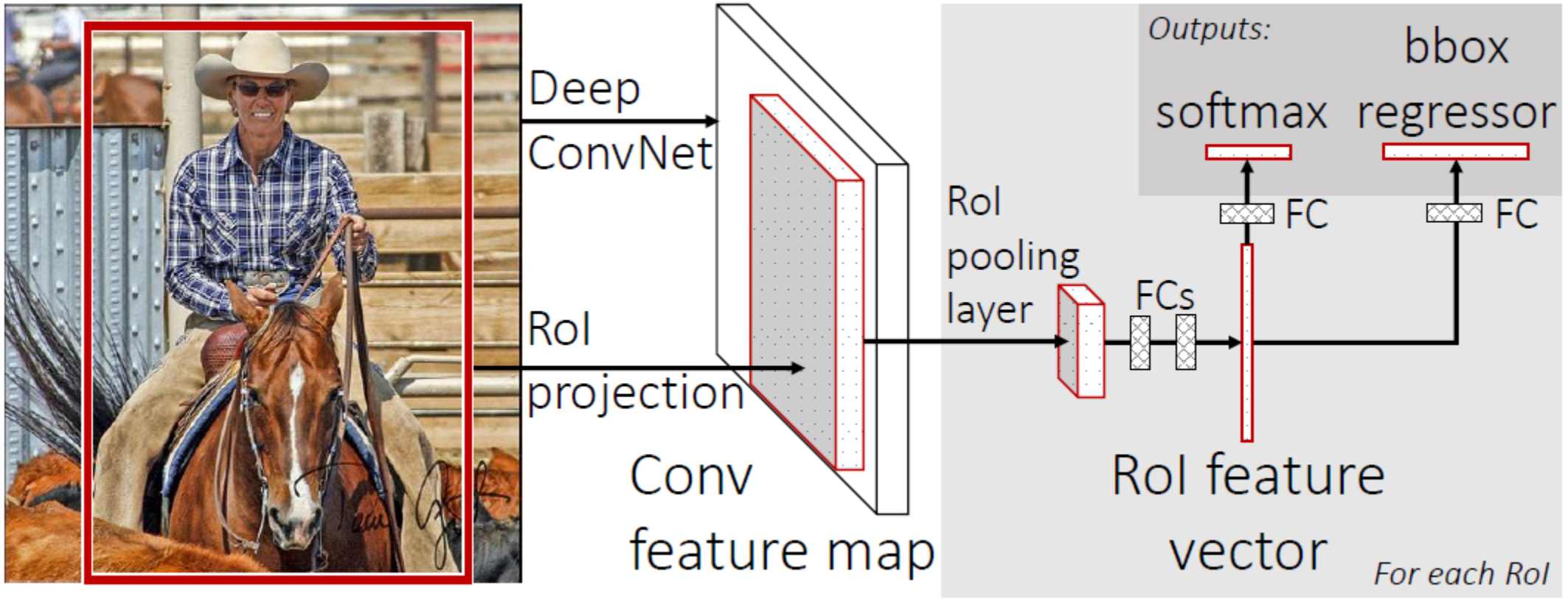
Problems of R-CNN

- Slow at test-time: need to run full forward path of CNN for each region proposal
  - 13s/image on a GPU(K40)
  - 53s/image on a CPU
- SVM and regressors are post-hoc: CNN features not updated in response to SVMs and regressors
- Complex multistage training pipeline (84 hours using K40 GPU)
  - Fine-tune network with softmax classifier(log loss)
  - Train post-hoc linear SVMs(hinge loss)
  - Train post-hoc bounding-box regressions(squared loss)

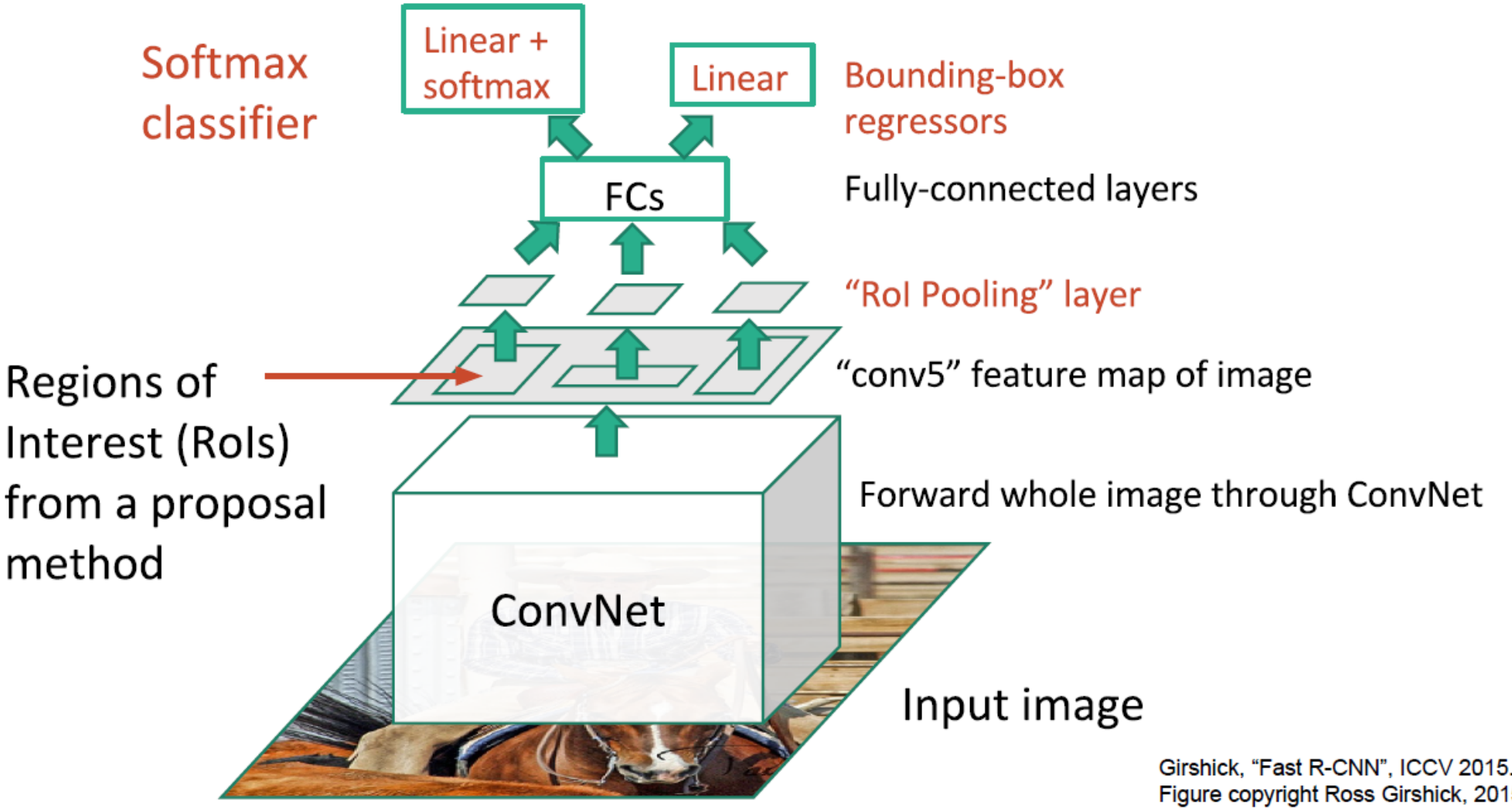
Fast R-CNN

- Fix most of what's wrong with R-CNN and SPP-net
- Train the detector in a single stage, end-to-end
  - No caching features to disk
  - No post hoc training steps
- Train all layers of the network

Fast R-CNN Architecture



Fast R-CNN

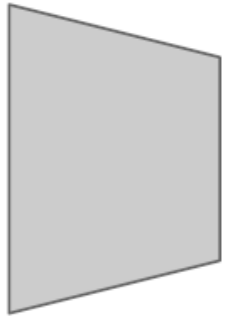


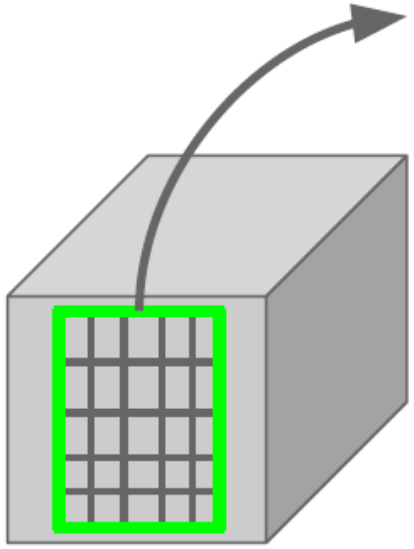
Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015;

RoI Pooling

Hi-res input image:
3 x 800 x 600
with region
proposal

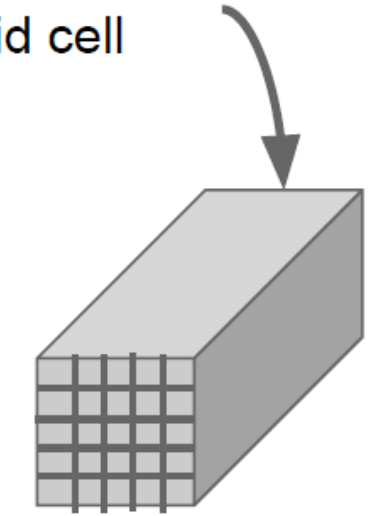
Convolution
and Pooling





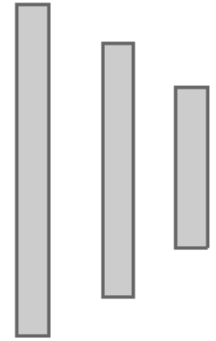
Hi-res conv features:
C x H x W
with region proposal

Max-pool within
each grid cell



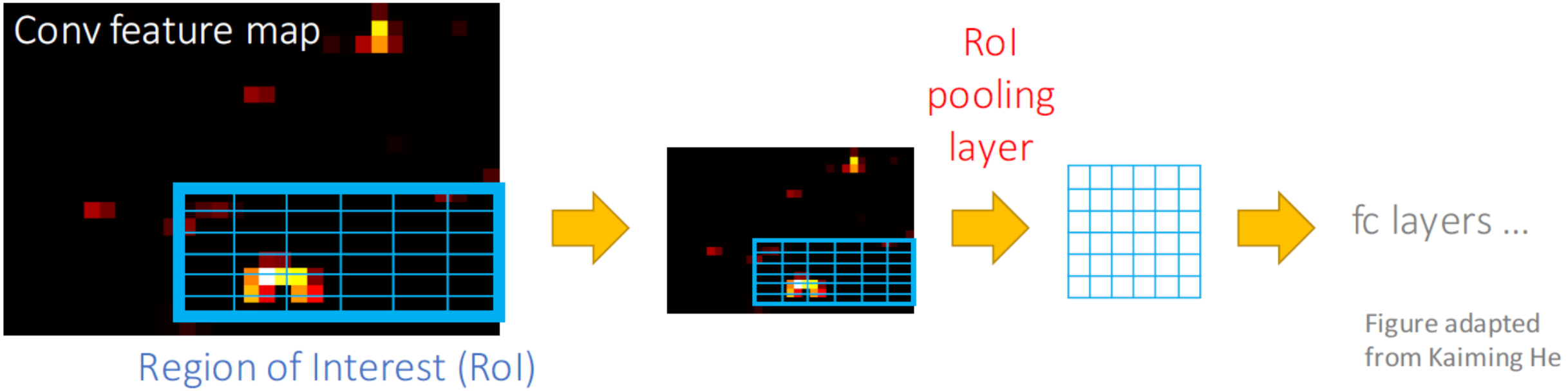
RoI conv features:
C x h x w
for region proposal

Fully-connected
layers



Fully-connected layers expect
low-res conv features:
C x h x w

RoI Pooling



Just a special case of the SPP layer with one pyramid level

RoI in Conv feature map : 21x14 → 3x2 max pooling with stride(3, 2) → output : 7x7
RoI in Conv feature map : 35x42 → 5x6 max pooling with stride(5, 6) → output : 7x7

Training & Testing

1. Takes an input and a set of bounding boxes
2. Generate convolutional feature maps
3. For each bbox, get a fixed-length feature vector from RoI pooling layer
4. Outputs have two information
   - K+1 class labels
   - Bounding box locations

- Loss function

True box coordinates

Predicted box coordinates

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

Predicted class scores

True class scores

Log loss

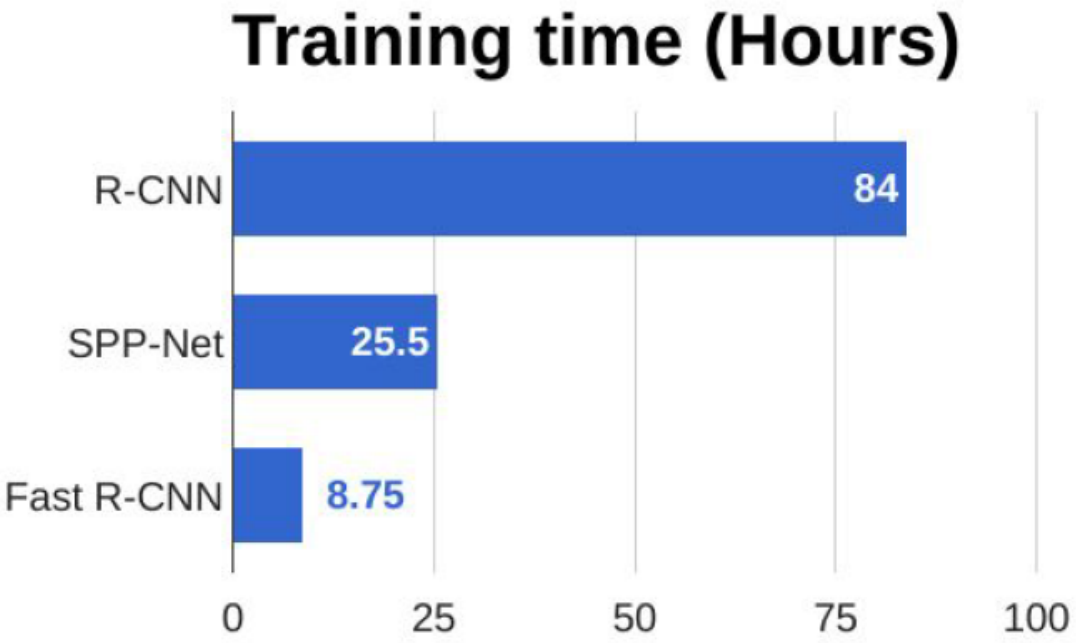
Smooth L1 loss

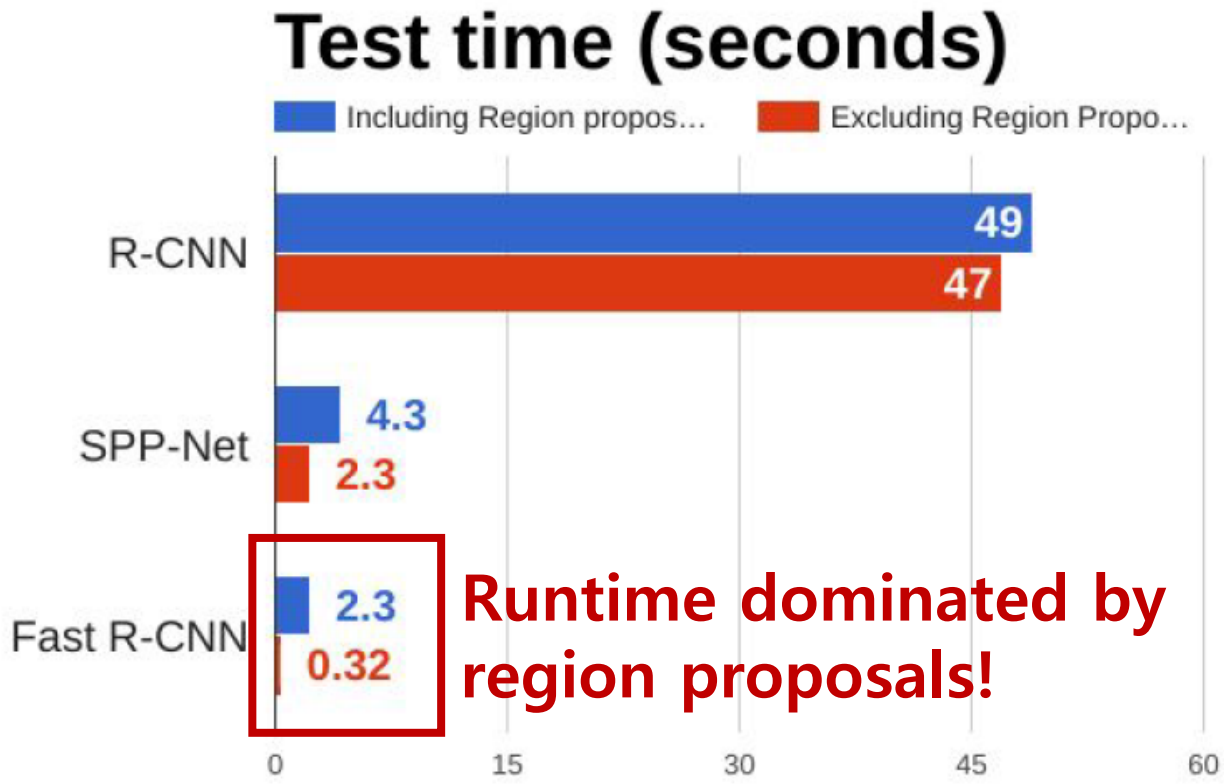
$$L_{\text{loc}}(t^u, v) = \sum_{i \in \{\text{x,y,w,h}\}} \text{smooth}_{L_1}(t_i^u - v_i),$$

in which

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

R-CNN vs SPP-net vs Fast R-CNN





Experimental Findings

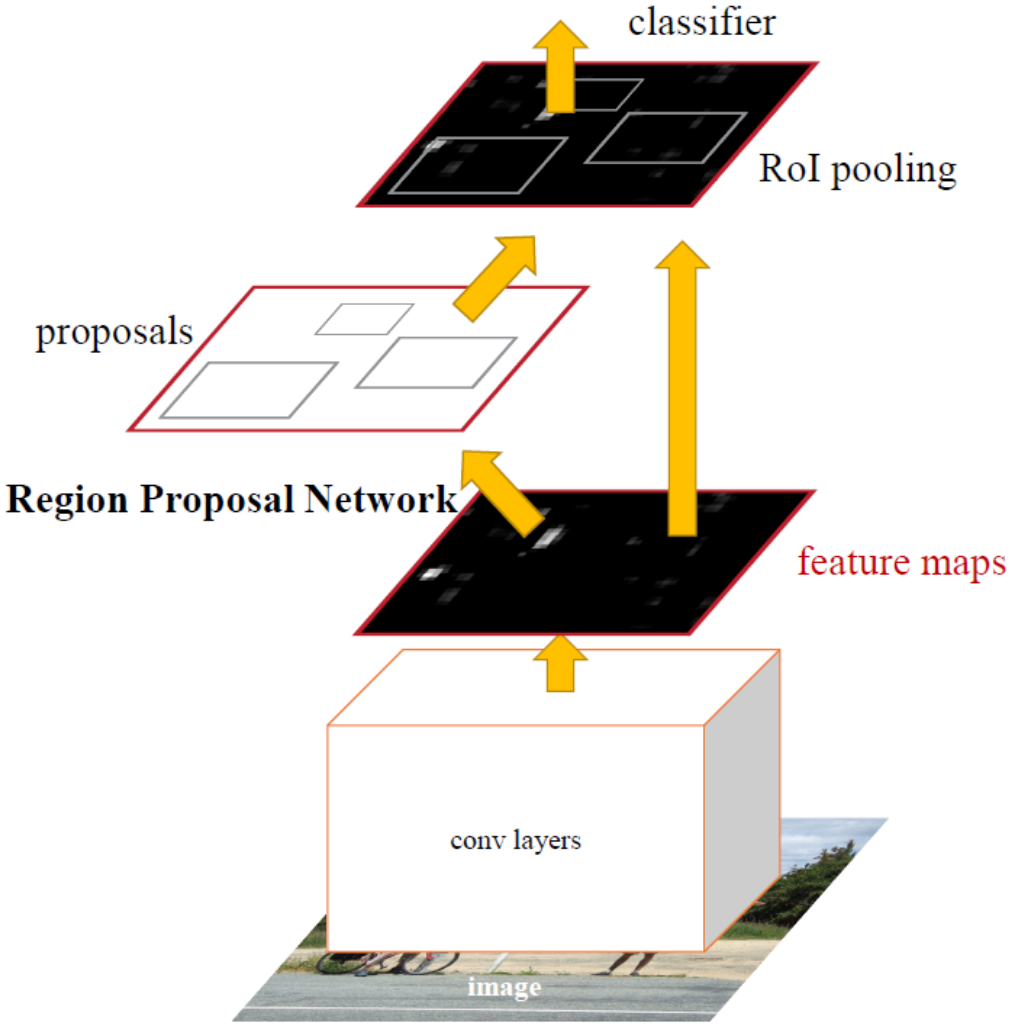
- End-to-end training is important for very deep networks
- Softmax is a fine replacement for SVMs
- Multi-task training is beneficial
- Single-scale testing is a good tradeoff
- Fast training and testing enables new experiments

Problems of Fast R-CNN

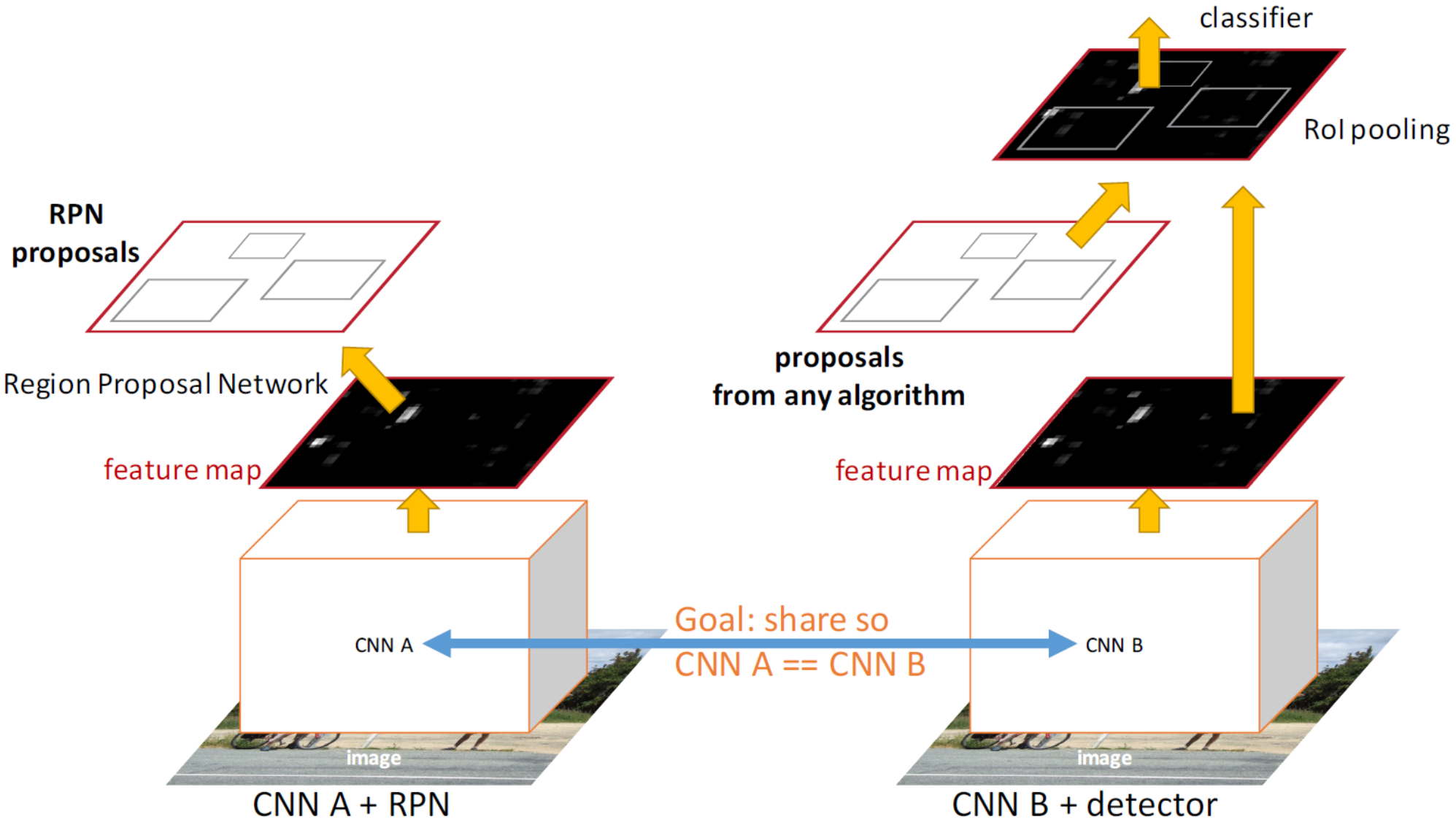
- Out-of-network region proposals are the test-time computational bottleneck
- Is it fast enough??

Faster R-CNN(RPN + Fast R-CNN)

- Insert a Region Proposal Network (RPN) after the last convolutional layer → using GPU!
- RPN trained to produce region proposals directly; no need for external region proposals
- After RPN, use RoI Pooling and an upstream classifier and bbox regressor just like Fast R-CNN

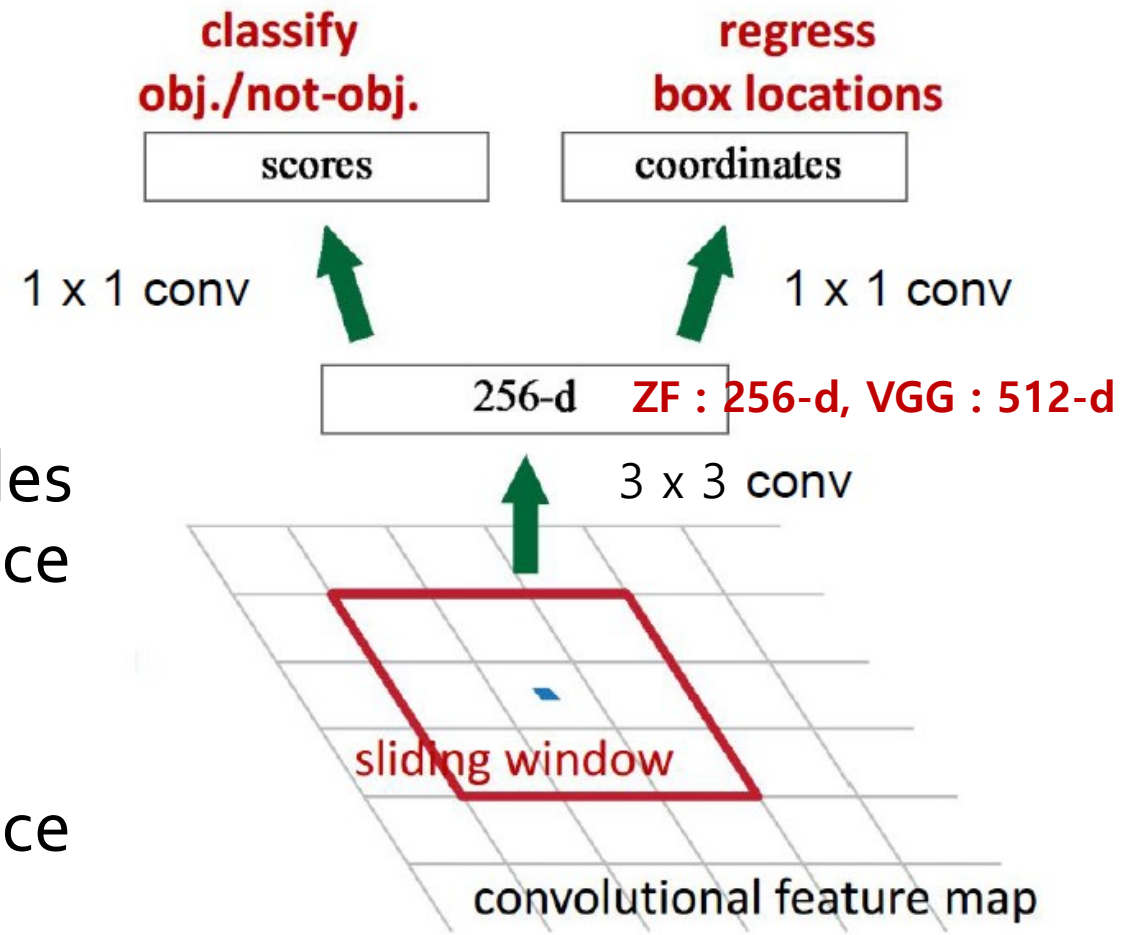


Training Goal : Share Features



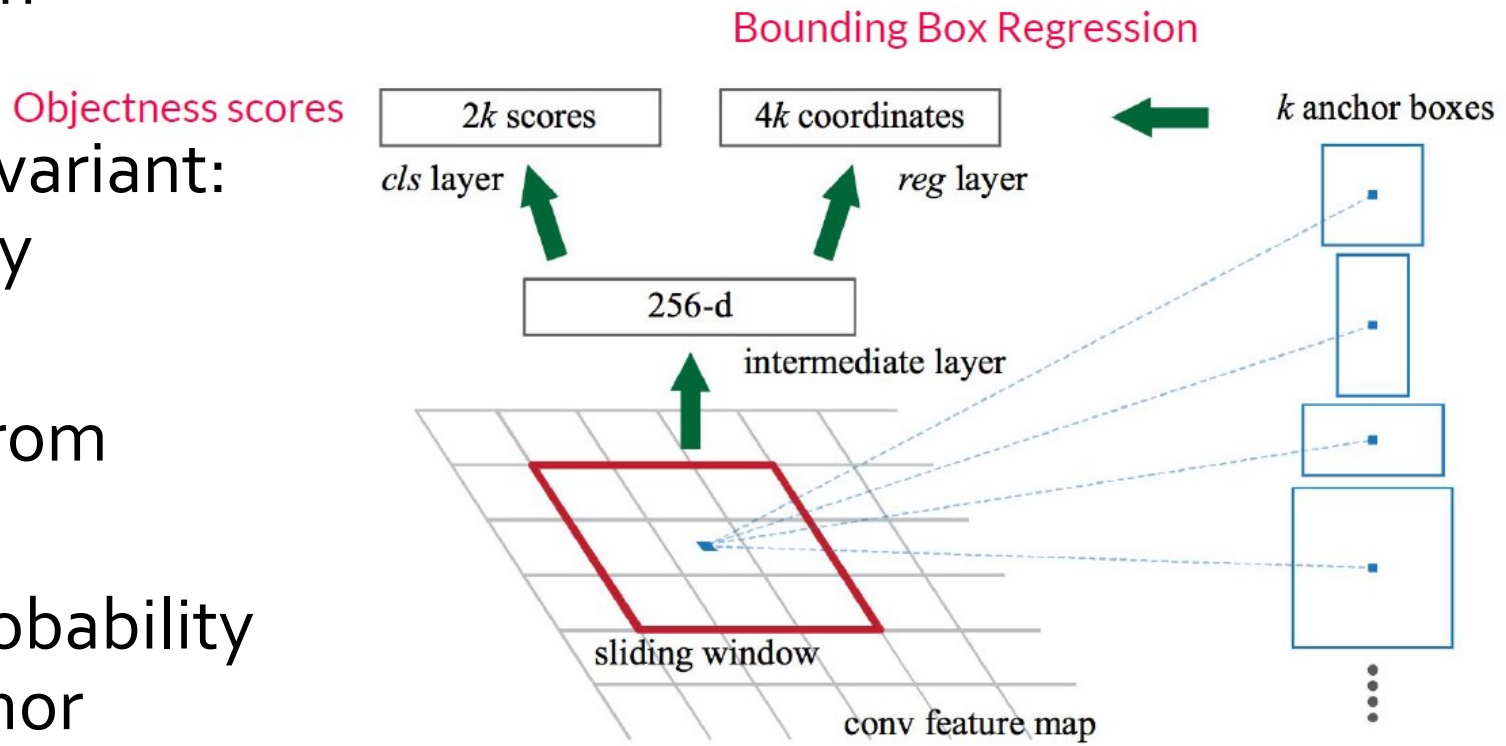
RPN

- Slide a small window on the feature map
- Build a small network for
  - Classifying object or not-object
  - Regressing bbox locations
- Position of the sliding window provides localization information with reference to the image
- Box regression provides finer localization information with reference to this sliding window



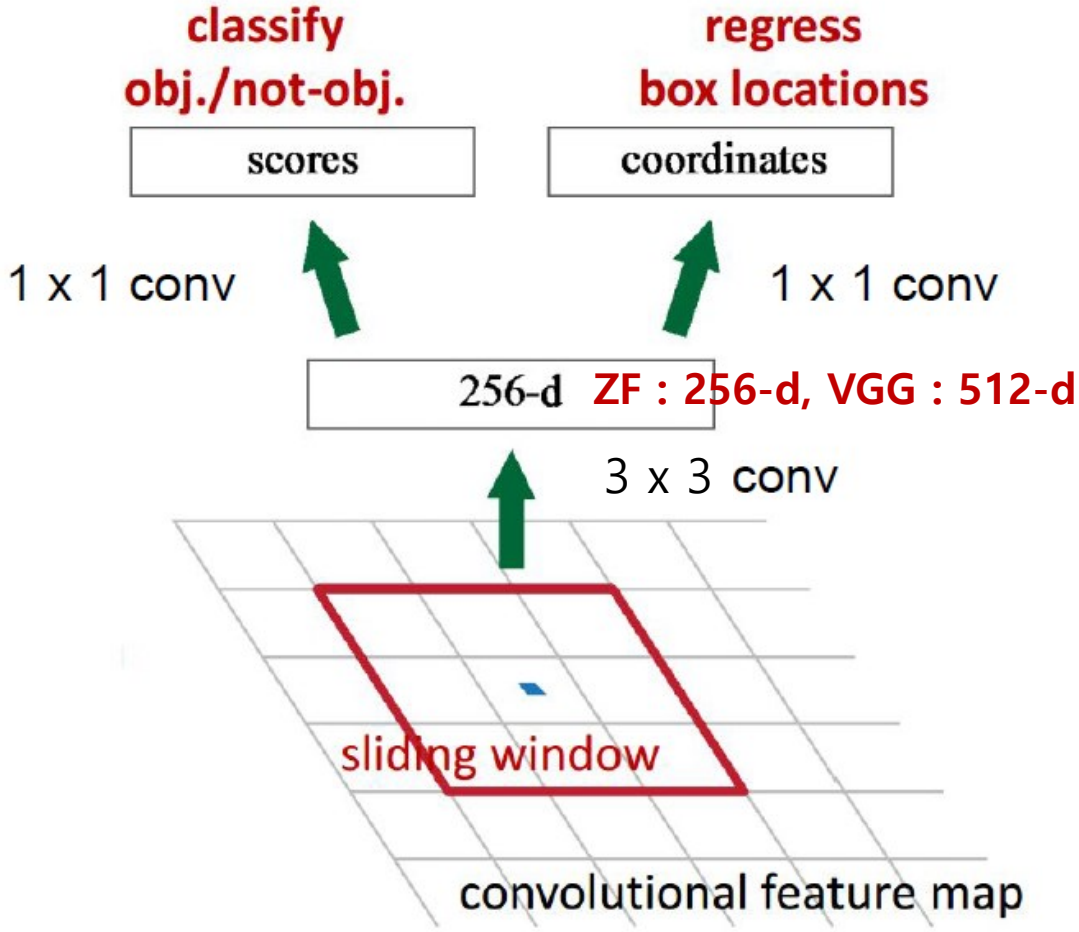
RPN

- Use k anchor boxes at each location
- Anchors are translation invariant: use the same ones at every location
- Regression gives offsets from anchor boxes
- Classification gives the probability that each (regressed) anchor shows an object



RPN(Fully Convolutional Network)

- Intermediate Layer – 256(or 512) 3x3 filter, stride 1, padding 1
- Cls layer – 18(9x2) 1x1 filter, stride 1, padding 0
- Reg layer – 36(9x4) 1x1 filter, stride 1, padding 0



Anchors as references

- Anchors: pre-defined reference boxes
- Multi-scale/size anchors:
  - Multiple anchors are used at each position:
    - 3 scale(128x128, 256x256, 512x512) and 3 aspect rations(2:1, 1:1, 1:2) yield 9 anchors
  - Each anchor has its own prediction function
  - Single-scale features, multi-scale predictions

Positive/Negative Samples

- An anchor is labeled as positive if
  - The anchor is the one with highest IoU overlap with a ground-truth box
  - The anchor has an IoU overlap with a ground-truth box higher than 0.7
- Negative labels are assigned to anchors with IoU lower than 0.3 for all ground-truth boxes
- 50%/50% ratio of positive/negative anchors in a minibatch

RPN Loss Function

i = anchor index in minibatch

Log loss

Ground truth objectness label

Smooth L1 loss

$$L(\{p_i\}, \{t_i\}) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*).$$

True box coordinates

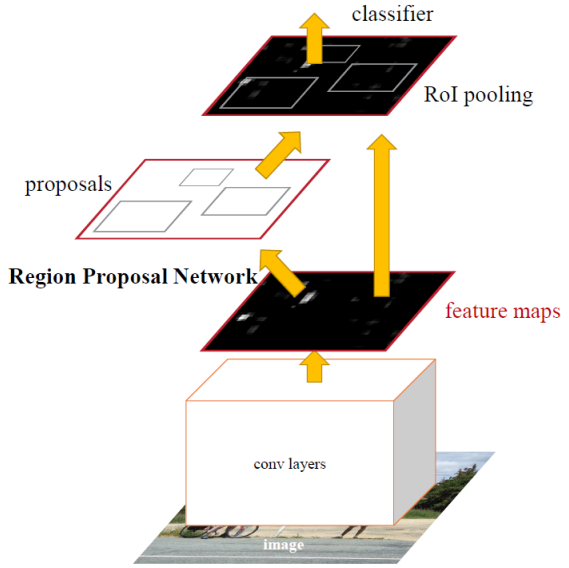
Coordinates of the predicted bounding box for anchor *i*

Predicted probability of being an object for anchor *i*

In practice $\lambda = 10$, so that both terms are roughly equally balanced

N_{cls} = Number of anchors in minibatch (~ 256)
N_{reg} = Number of anchor locations (~ 2400)

4-Step Alternating Training




```
# Let M0 be an ImageNet pre-trained network

1.  train_rpn(M0) → M1                  # Train an RPN initialized from M0, get M1

2.  generate_proposals(M1) → P1         # Generate training proposals P1 using RPN M1

3.  train_fast_rcnn(M0, P1) → M2        # Train Fast R-CNN M2 on P1 initialized from M0

4.  train_rpn_frozen_conv(M2) → M3      # Train RPN M3 from M2 without changing conv layers

5.  generate_proposals(M3) → P2

6.  train_fast_rcnn_frozen_conv(M3, P2) → M4   # Conv layers are shared with RPN M3

7.  return add_rpn_layers(M4, M3.RPN)          # Add M3's RPN layers to Fast R-CNN M4
```

Results

	R-CNN	Fast R-CNN	Faster R-CNN
Test time per image (with proposals)	50 seconds	2 seconds	**0.2 seconds**
(Speedup)	1x	25x	**250x**
mAP (VOC 2007)	66.0	**66.9**	**69.9**

Table 5: **Timing** (ms) on a K40 GPU, except SS proposal is evaluated in a CPU. "Region-wise" includes NMS, pooling, fully-connected, and softmax layers. See our released code for the profiling of running time.

model	system	conv	proposal	region-wise	total	rate
VGG	SS + Fast R-CNN	146	1510	174	1830	0.5 fps
VGG	RPN + Fast R-CNN	141	**10**	47	**198**	**5 fps**
ZF	RPN + Fast R-CNN	31	**3**	25	**59**	**17 fps**

Experiments

Table 1: the learned average proposal size for each anchor using the ZF net (numbers for $s = 600$).

anchor	128^2, 2:1	128^2, 1:1	128^2, 1:2	256^2, 2:1	256^2, 1:1	256^2, 1:2	512^2, 2:1	512^2, 1:1	512^2, 1:2
proposal	188×111	113×114	70×92	416×229	261×284	174×332	768×437	499×501	355×715

Table 8: Detection results of Faster R-CNN on PASCAL VOC 2007 test set using **different settings of anchors**. The network is VGG-16. The training data is VOC 2007 trainval. The default setting of using 3 scales and 3 aspect ratios (69.9%) is the same as that in Table 3.

settings	anchor scales	aspect ratios	mAP (%)
1 scale, 1 ratio	128^2	1:1	65.8
	256^2	1:1	66.7
1 scale, 3 ratios	128^2	{2:1, 1:1, 1:2}	68.8
	256^2	{2:1, 1:1, 1:2}	67.9
3 scales, 1 ratio	$\{128^2, 256^2, 512^2\}$	1:1	**69.8**
3 scales, 3 ratios	$\{128^2, 256^2, 512^2\}$	{2:1, 1:1, 1:2}	**69.9**

Table 9: Detection results of Faster R-CNN on PASCAL VOC 2007 test set using **different values of** λ in Equation (1). The network is VGG-16. The training data is VOC 2007 trainval. The default setting of using $\lambda = 10$ (69.9%) is the same as that in Table 3.

λ	0.1	1	10	100
mAP (%)	67.2	68.9	69.9	69.1

Experiments

Table 2: Detection results on **PASCAL VOC 2007 test set** (trained on VOC 2007 trainval). The detectors are Fast R-CNN with ZF, but using various proposal methods for training and testing.

train-time region proposals		**test-time region proposals**		
method	# boxes	method	# proposals	mAP (%)
SS	2000	SS	2000	58.7
EB	2000	EB	2000	58.6
RPN+ZF, shared	2000	RPN+ZF, shared	300	**59.9**
ablation experiments follow below				
RPN+ZF, unshared	2000	RPN+ZF, unshared	300	58.7
SS	2000	RPN+ZF	100	55.1
SS	2000	RPN+ZF	300	56.8
SS	2000	RPN+ZF	1000	56.3
SS	2000	RPN+ZF (no NMS)	6000	55.2
SS	2000	RPN+ZF (no *cls*)	100	44.6
SS	2000	RPN+ZF (no *cls*)	300	51.4
SS	2000	RPN+ZF (no *cls*)	1000	55.8
SS	2000	RPN+ZF (no *reg*)	300	52.1
SS	2000	RPN+ZF (no *reg*)	1000	51.3
SS	2000	RPN+VGG	300	59.2

Experiments

Table 3: Detection results on **PASCAL VOC 2007 test set**. The detector is Fast R-CNN and VGG-16. Training data: "07": VOC 2007 trainval, "07+12": union set of VOC 2007 trainval and VOC 2012 trainval. For RPN, the train-time proposals for Fast R-CNN are 2000. †: this number was reported in [2]; using the repository provided by this paper, this result is higher (68.1).

method	# proposals	data	mAP (%)
SS	2000	07	66.9†
SS	2000	07+12	70.0
RPN+VGG, unshared	300	07	68.5
RPN+VGG, shared	300	07	69.9
RPN+VGG, shared	300	07+12	**73.2**
RPN+VGG, shared	300	COCO+07+12	**78.8**

Table 4: Detection results on **PASCAL VOC 2012 test set**. The detector is Fast R-CNN and VGG-16. Training data: "07": VOC 2007 trainval, "07++12": union set of VOC 2007 trainval+test and VOC 2012 trainval. For RPN, the train-time proposals for Fast R-CNN are 2000. †: http://host.robots.ox.ac.uk:8080/anonymous/HZJTQA.html. ‡: http://host.robots.ox.ac.uk:8080/anonymous/YNPLXB.html. §: http://host.robots.ox.ac.uk:8080/anonymous/XEDH10.html.

method	# proposals	data	mAP (%)
SS	2000	12	65.7
SS	2000	07++12	68.4
RPN+VGG, shared†	300	12	67.0
RPN+VGG, shared‡	300	07++12	**70.4**
RPN+VGG, shared§	300	COCO+07++12	**75.9**

Is It Enough?

- RoI Pooling has some quantization operations
- These quantizations introduce misalignments between the RoI and the extracted features
- While this may not impact classification, it can make a negative effect on predicting bbox

YOLO

YOLO

- You Only Look Once
- Quite similar with Faster R-CNN and very FAST!

Concepts

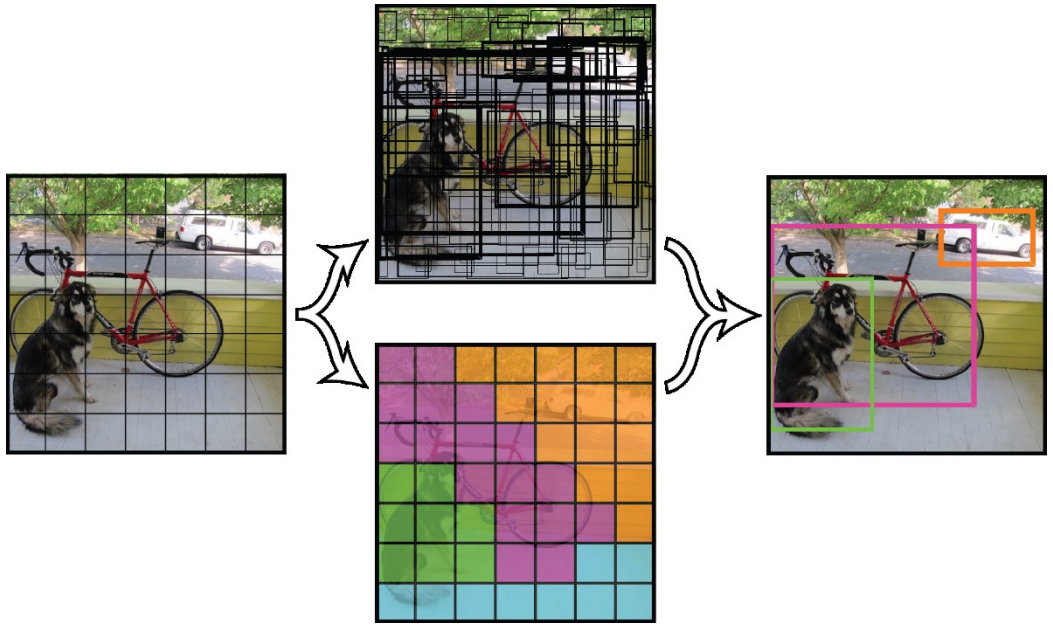
- Detection as Single Regression Problem
- Developed as Single Convolutional Network
- Reason Globally on the Entire Image
- Learns Generalizable Representations

Unified Detection

- Given an image, divide it into an SxS grid

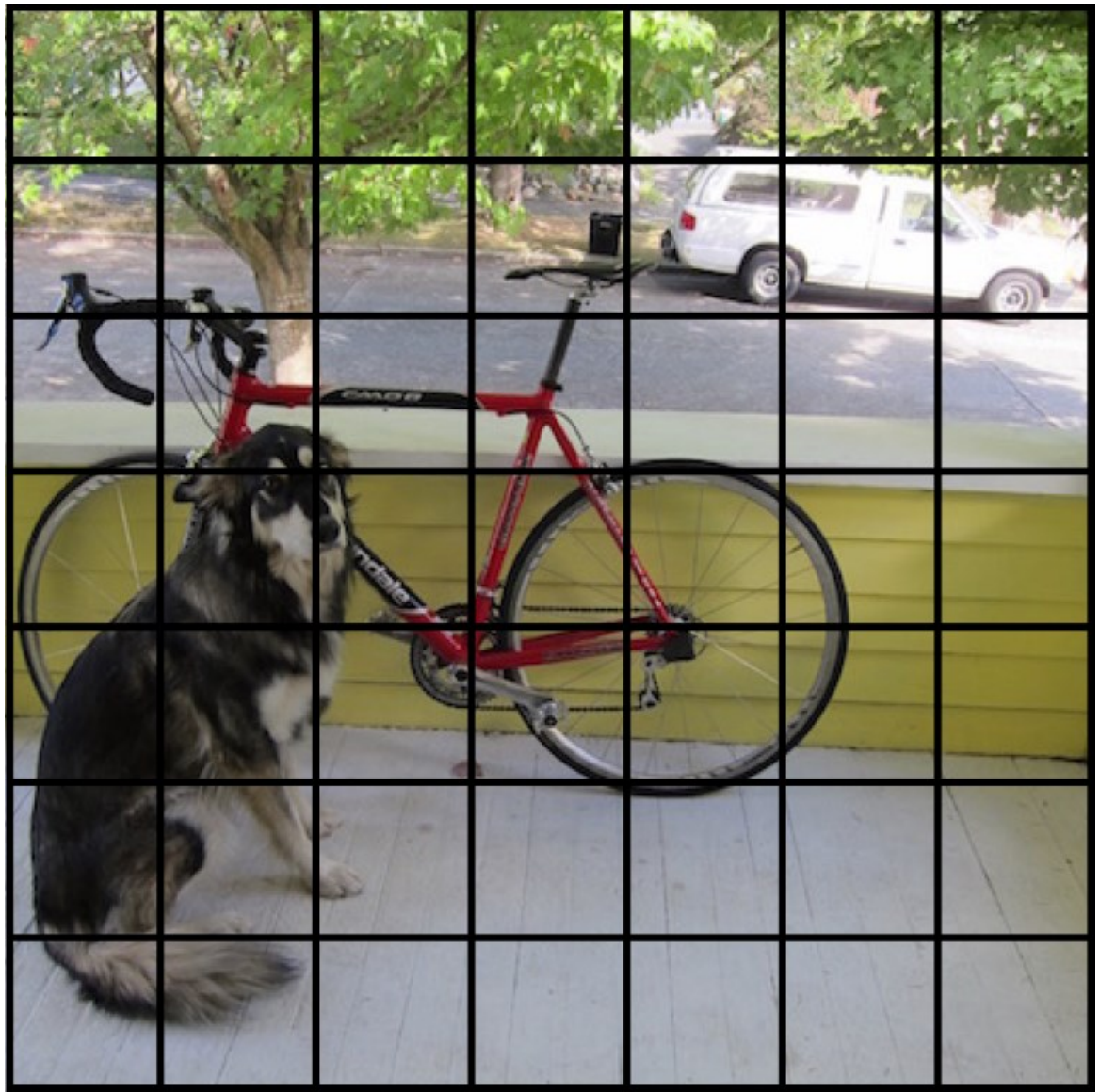
→If the center of an object falls into the grid cell, that grid cell is responsible

- Each cell predicts B bounding boxes
  - Five predictions: x, y, w, h, confidence
- Each cell predicts C class probabilities
  - Cell → C class probabilities, Bx5 bounding box informations
- One cell → One class probability
  - Low false positive!

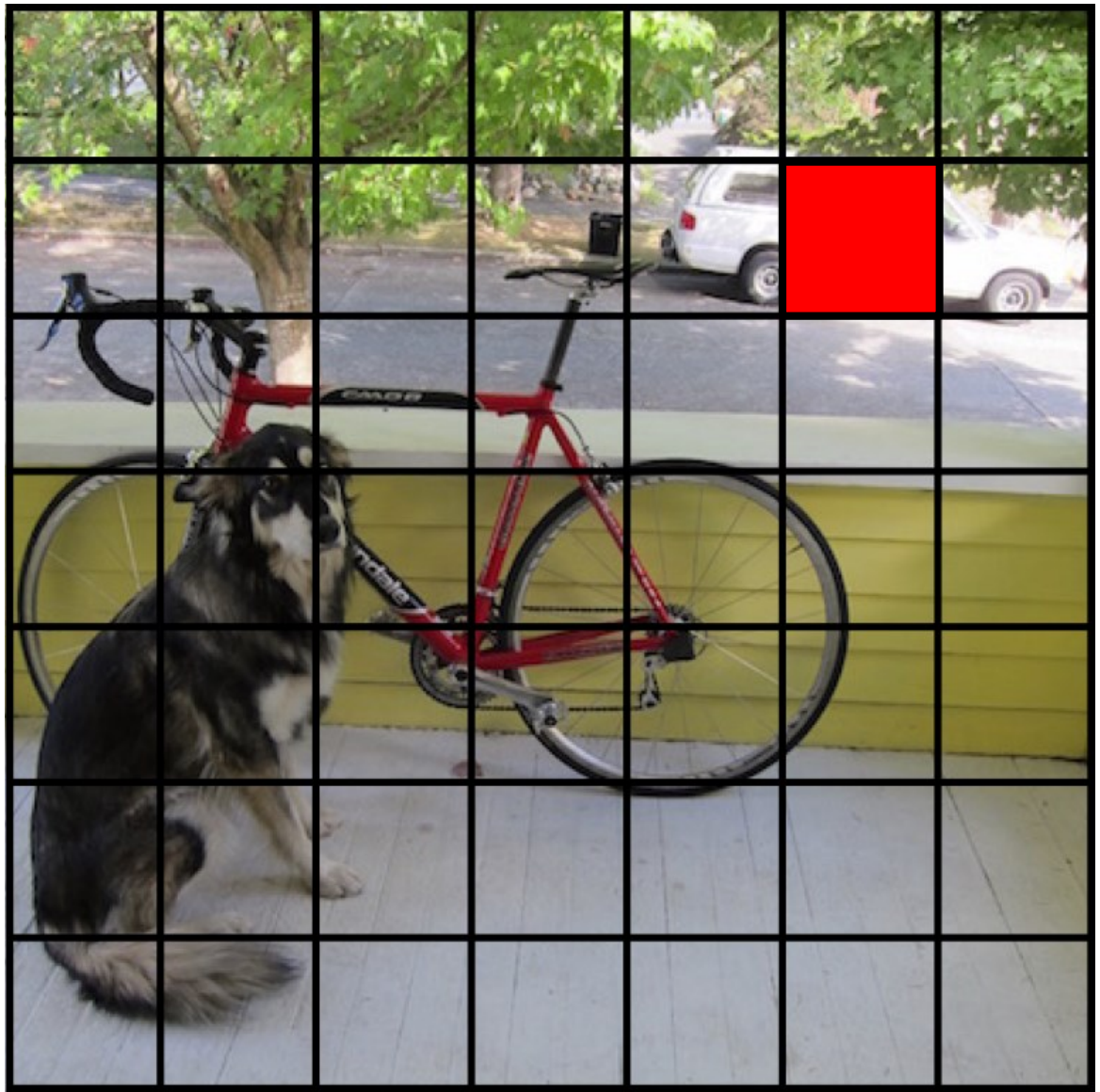


Detection Flow

Split the image into a grid(7x7)

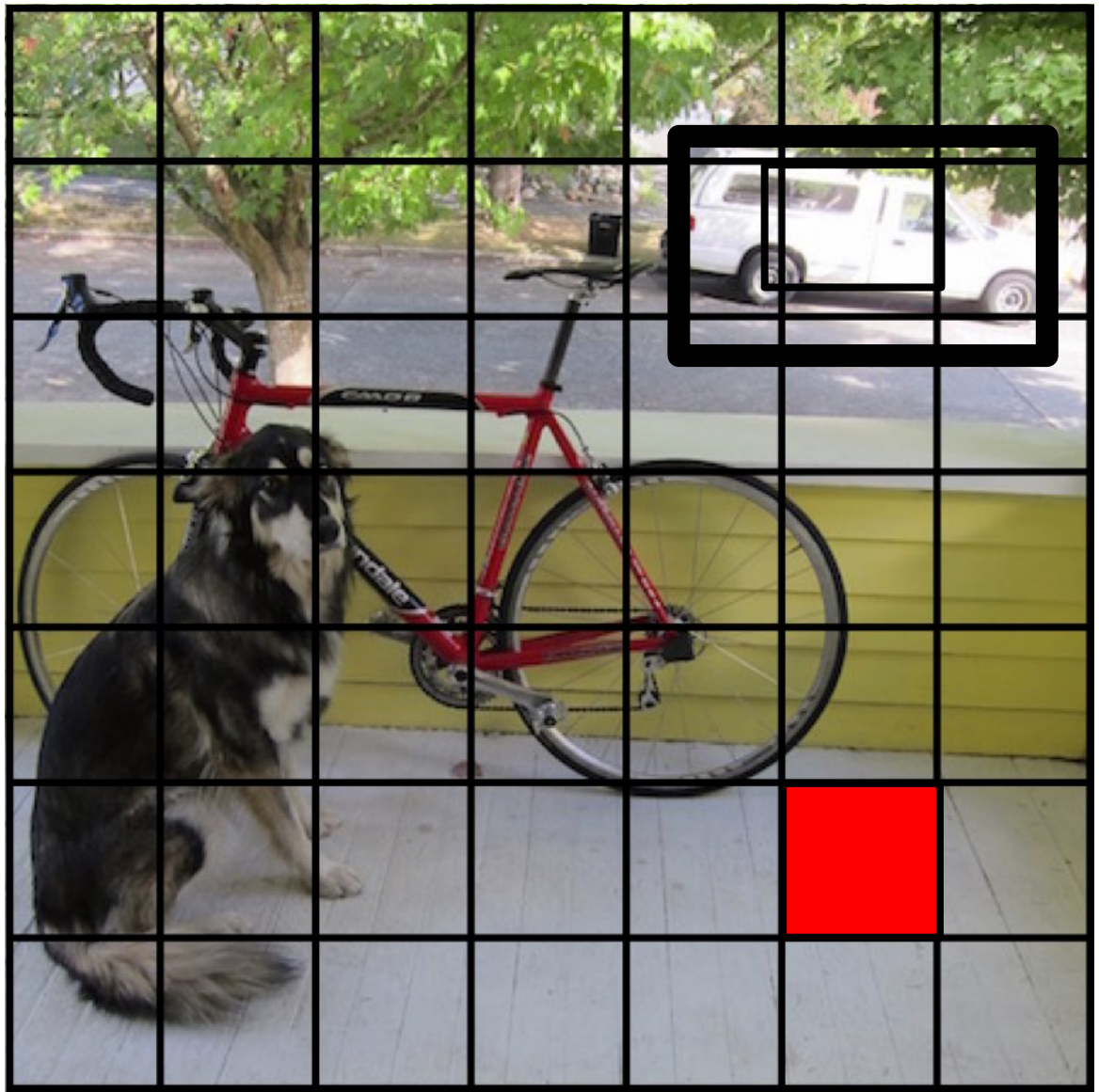


Each cell predicts boxes and confidences: P(Object)

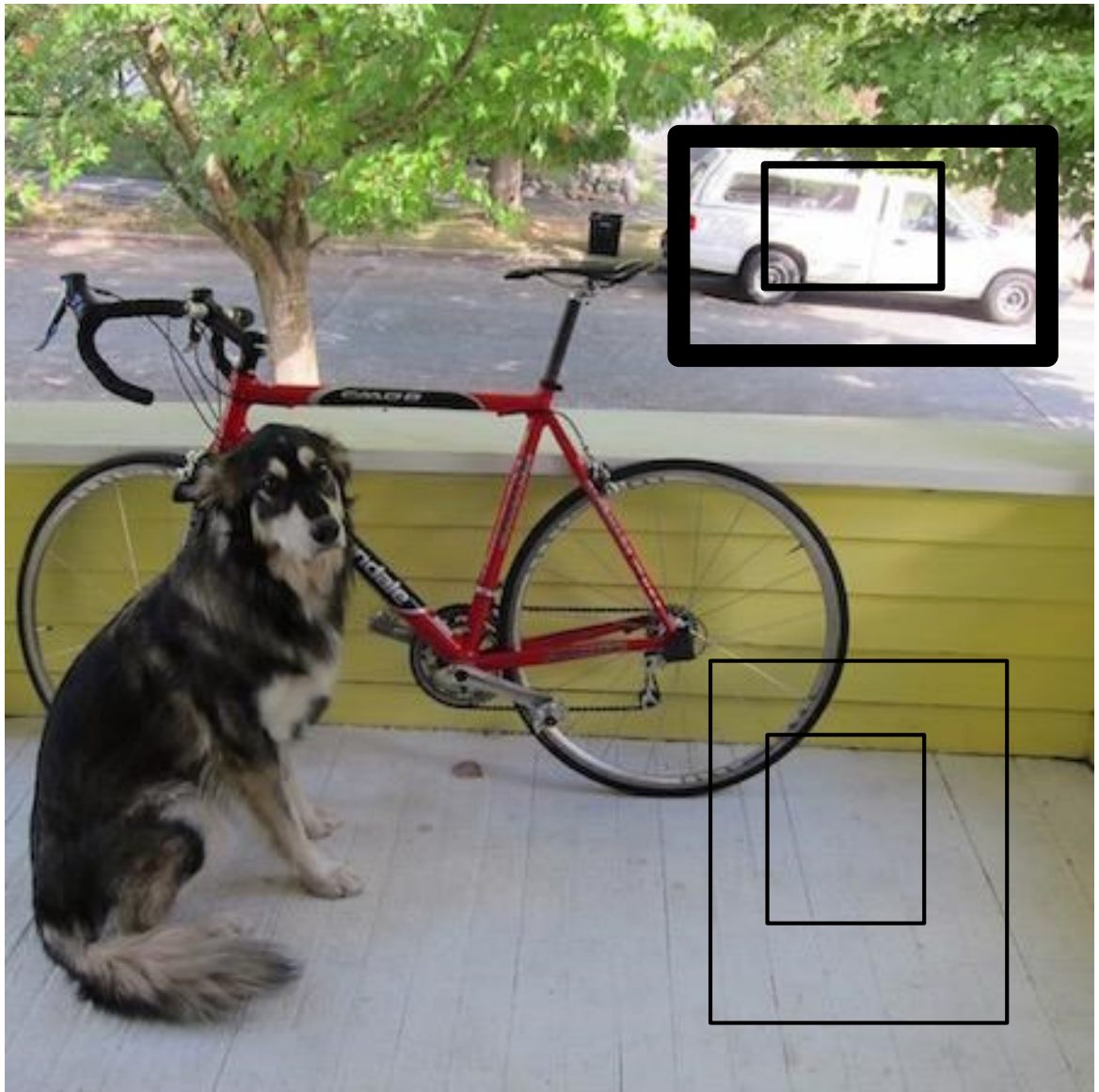


Each cell predicts boxes and confidences: P(Object)

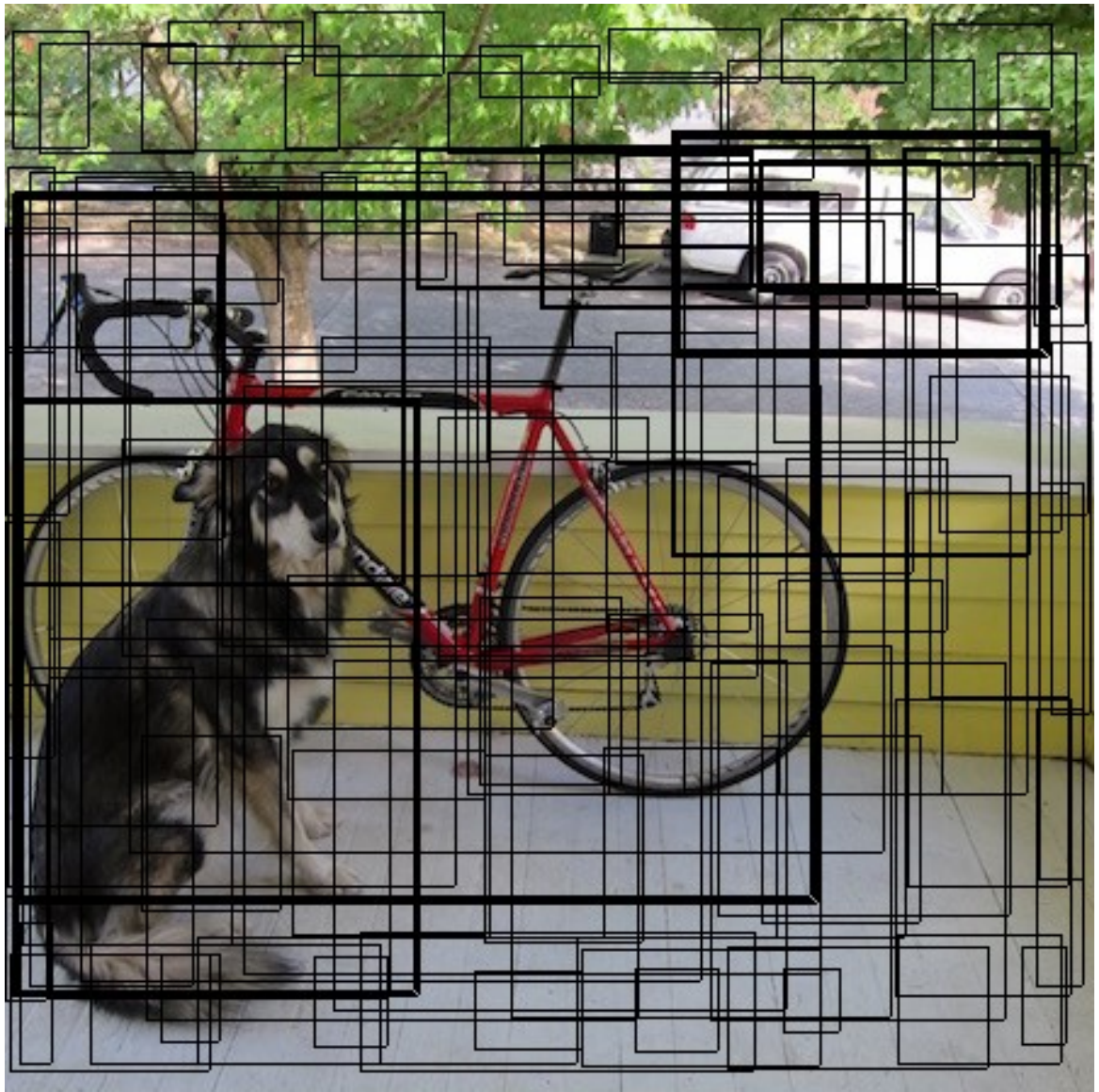
Each cell predicts boxes and confidences: P(Object)



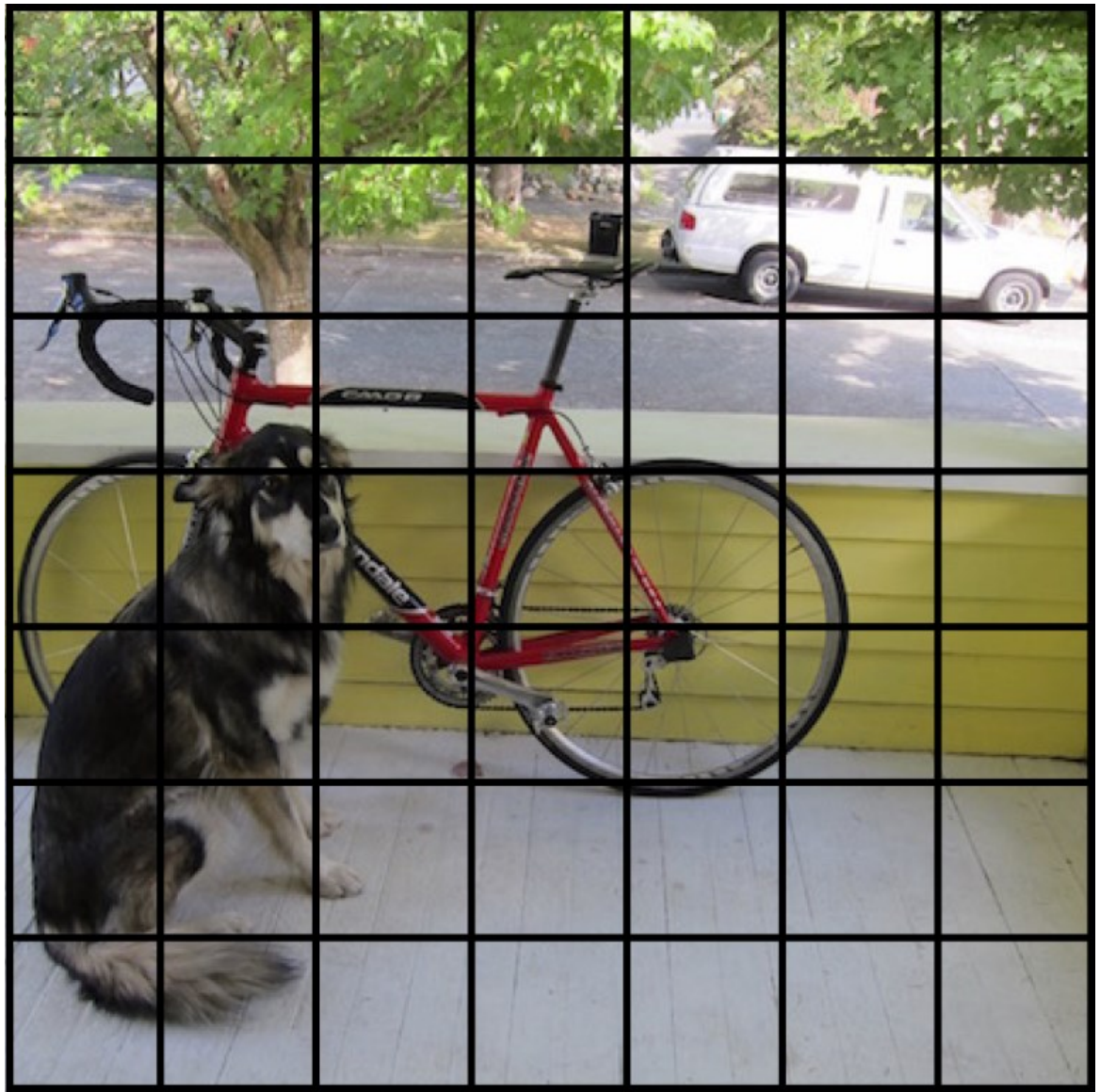
Each cell predicts boxes and confidences: P(Object)



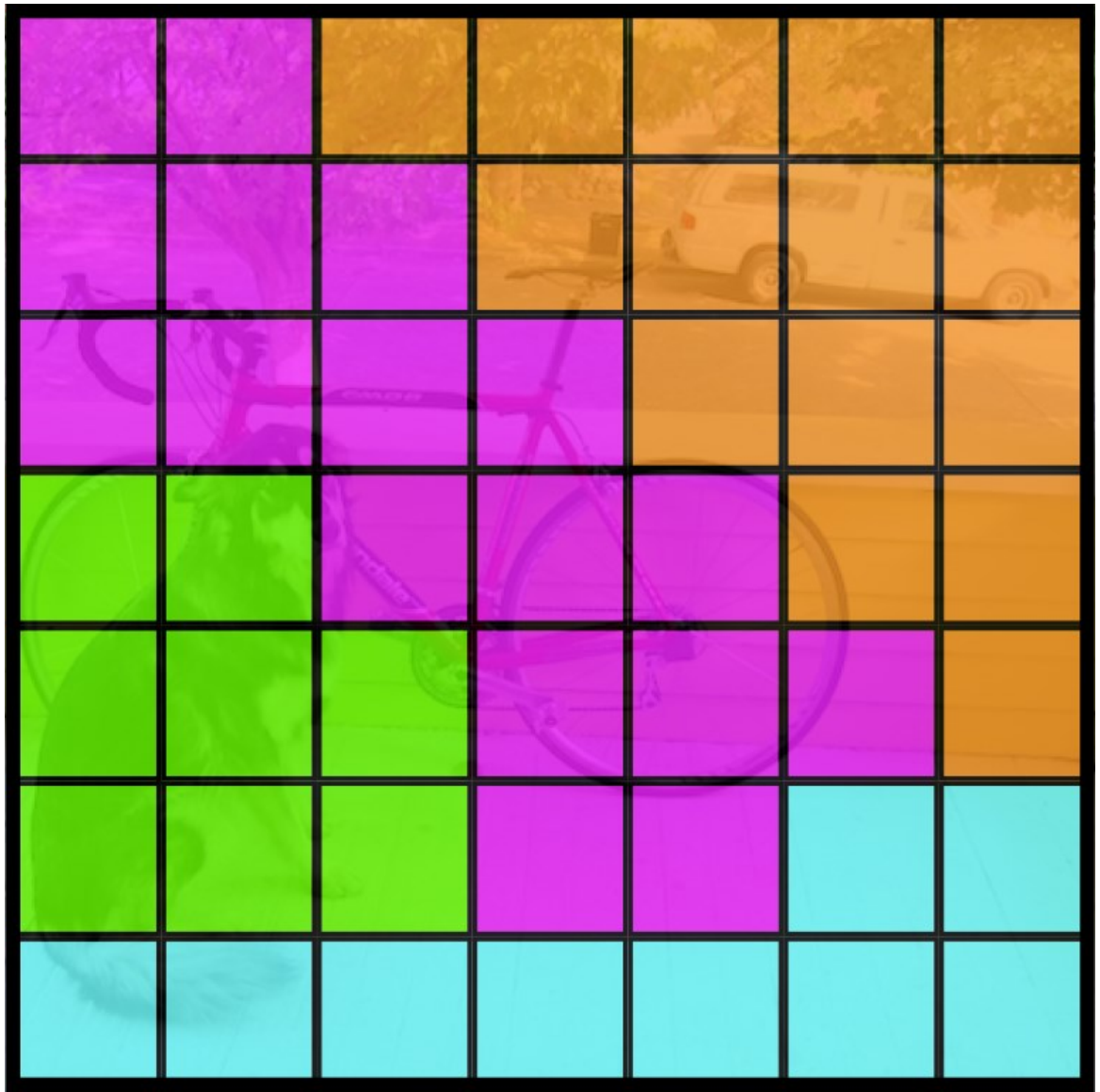
Each cell predicts boxes and confidences: P(Object)



Each cell also predicts a class probability



Each cell also predicts a class probability



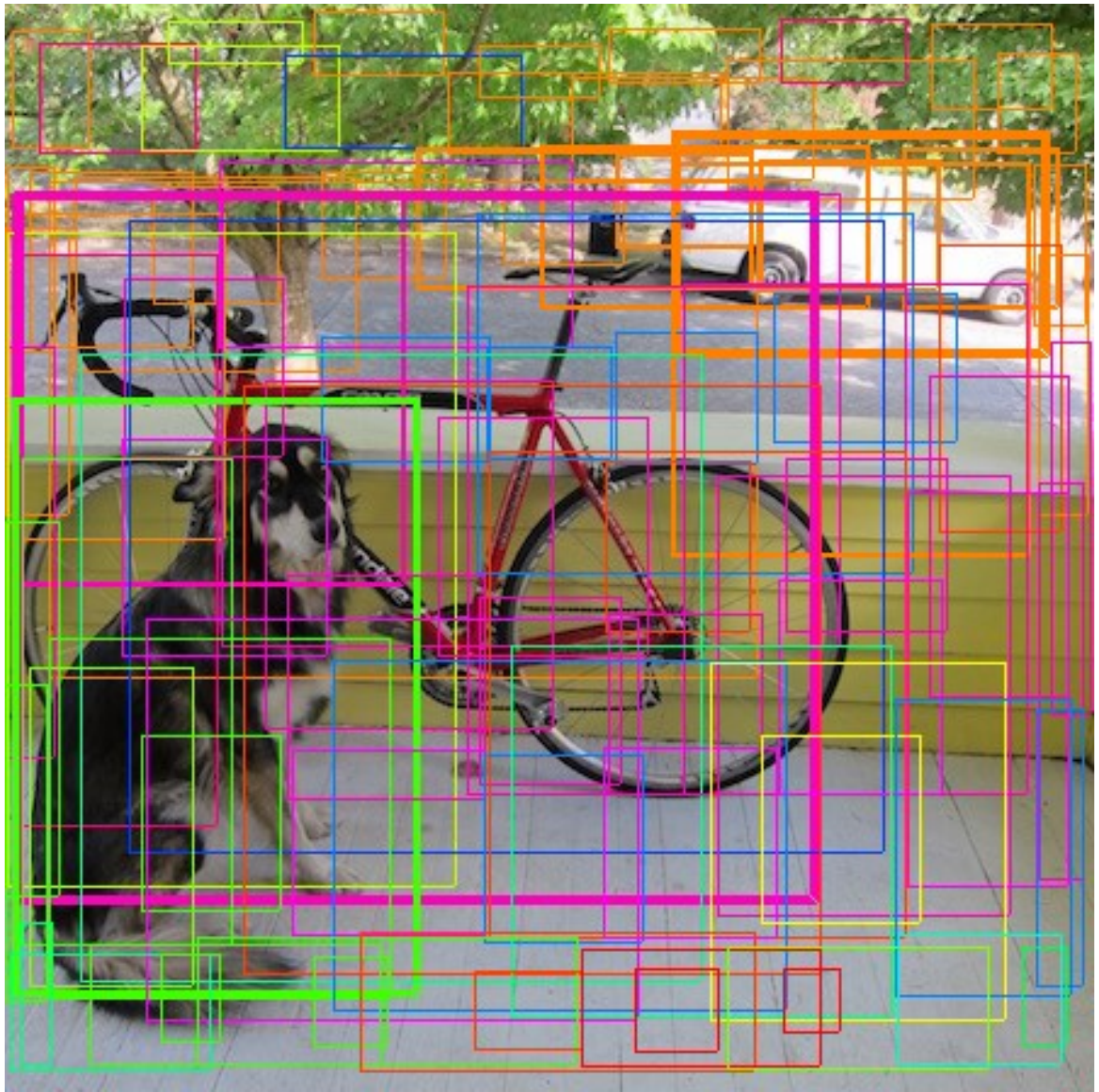
Bicycle

Car

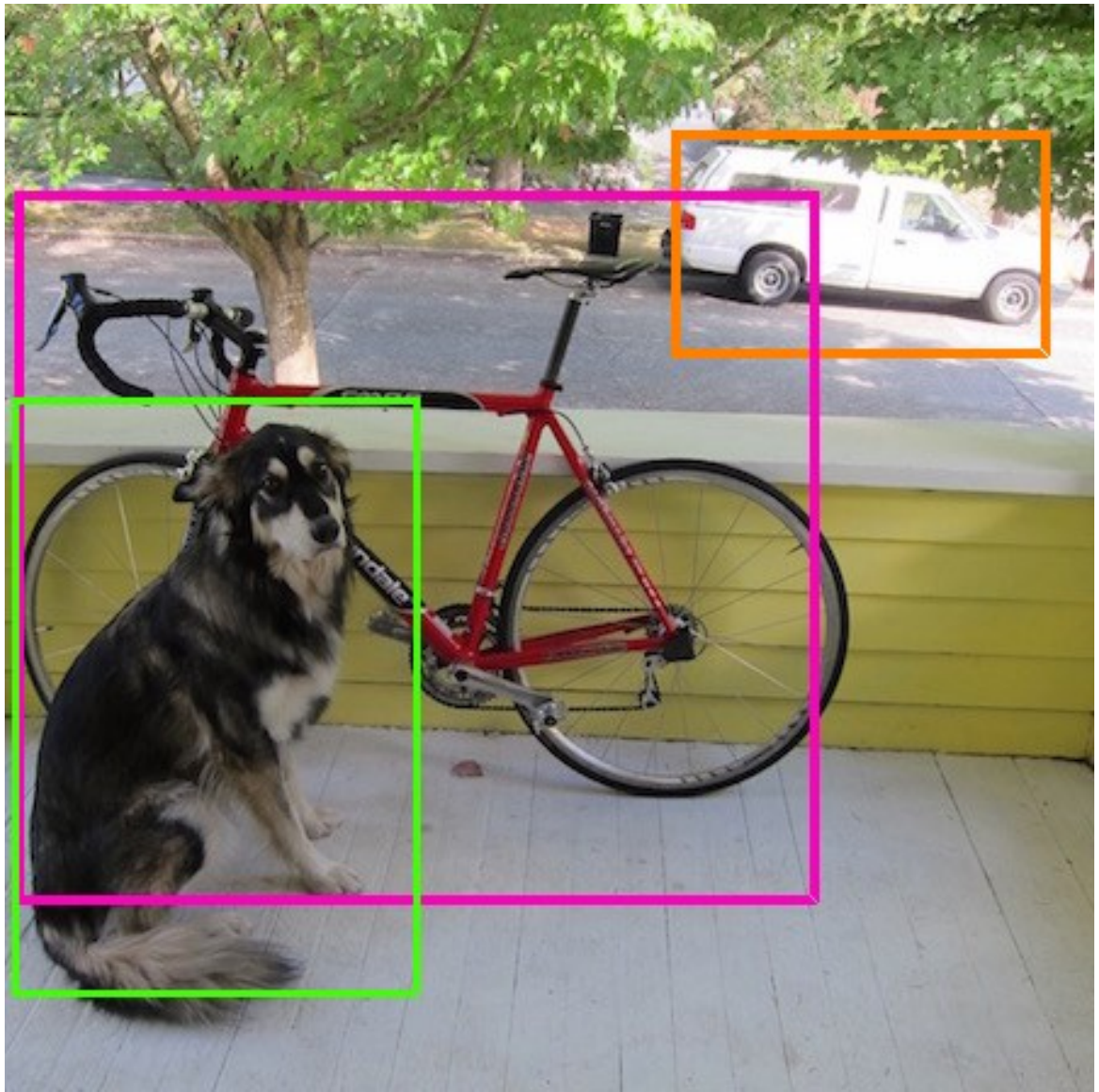
Dog

Dining Table

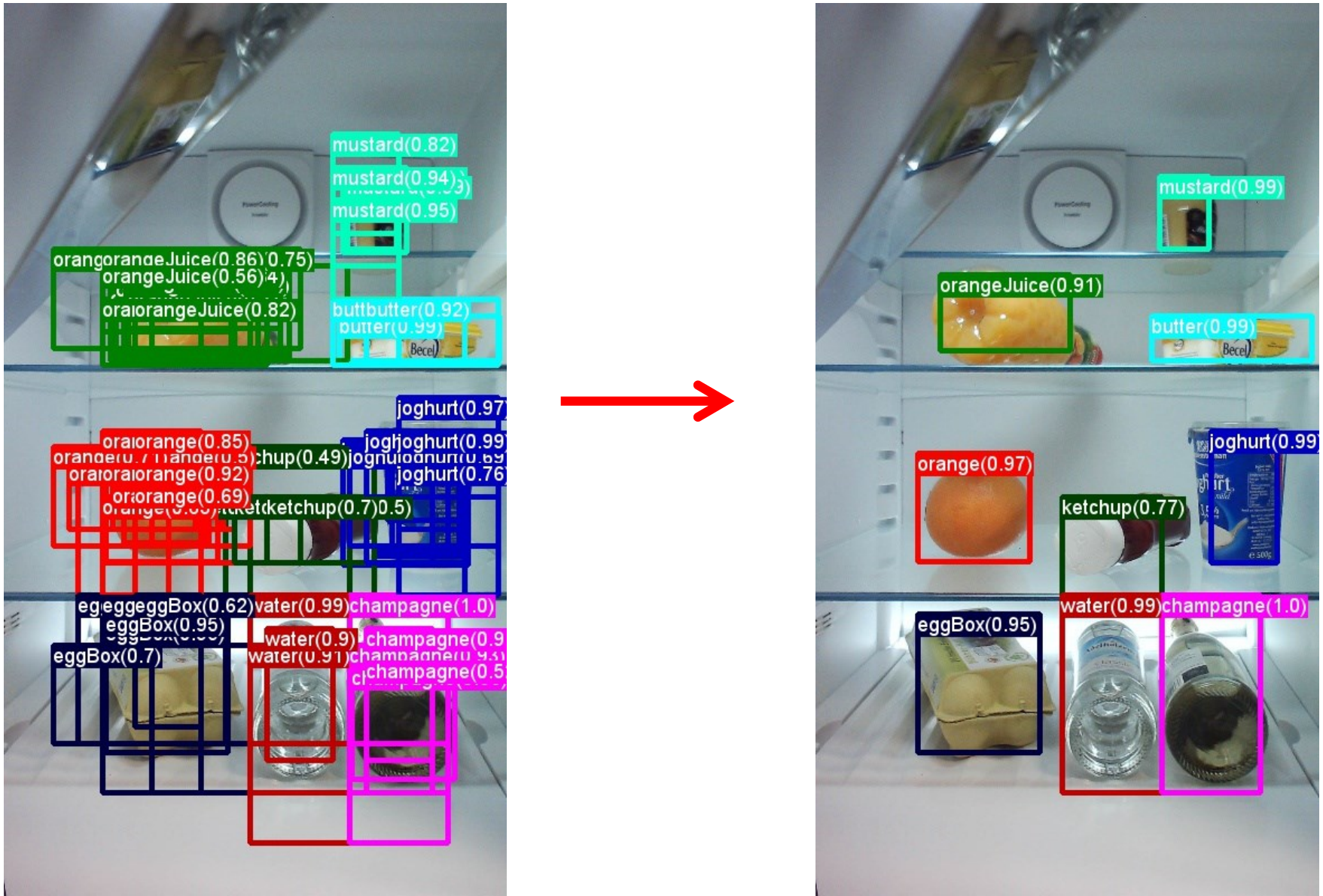
Then we combine the box and class predictions.



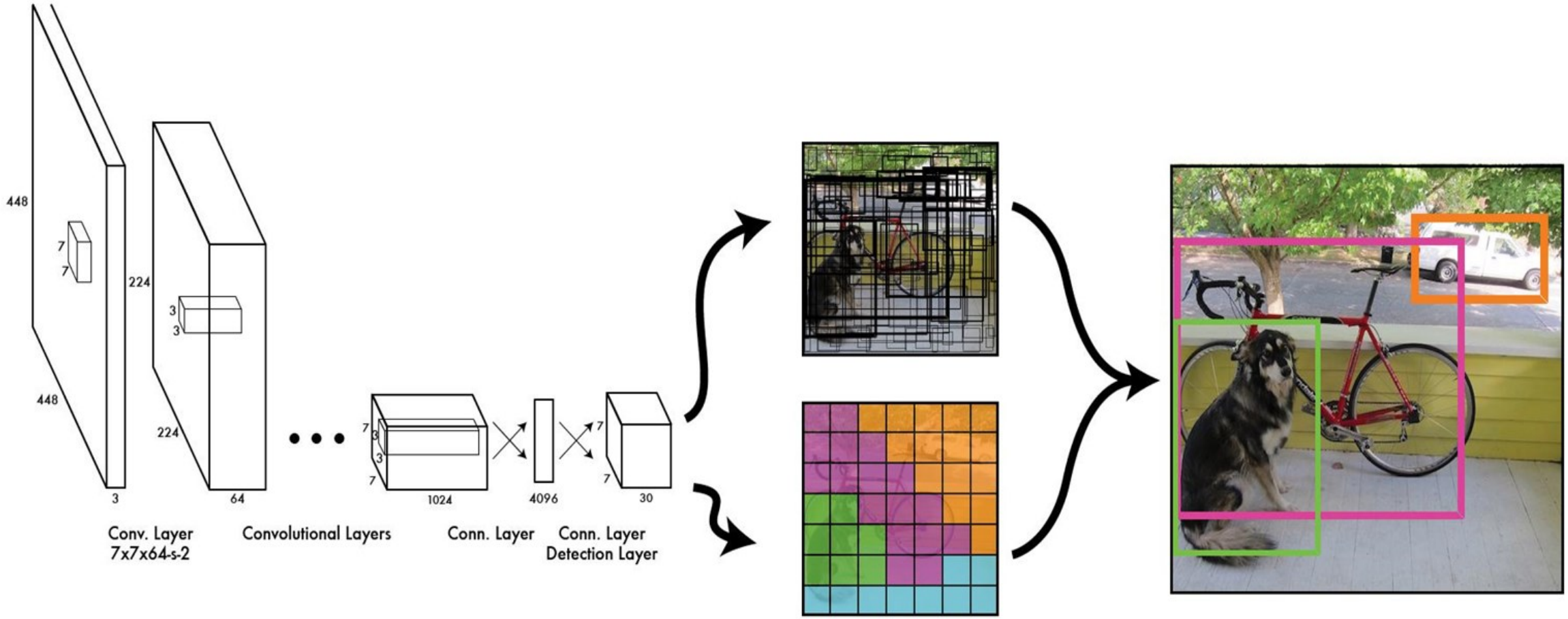
Finally we do NMS and threshold detections



Non-Maximum Suppresion



YOLO


448
448
7
7
224
224
3
3
3
64
1024
4096
30
Conv. Layer
7x7x64-s-2
Convolutional Layers
Conn. Layer
Conn. Layer
Detection Layer

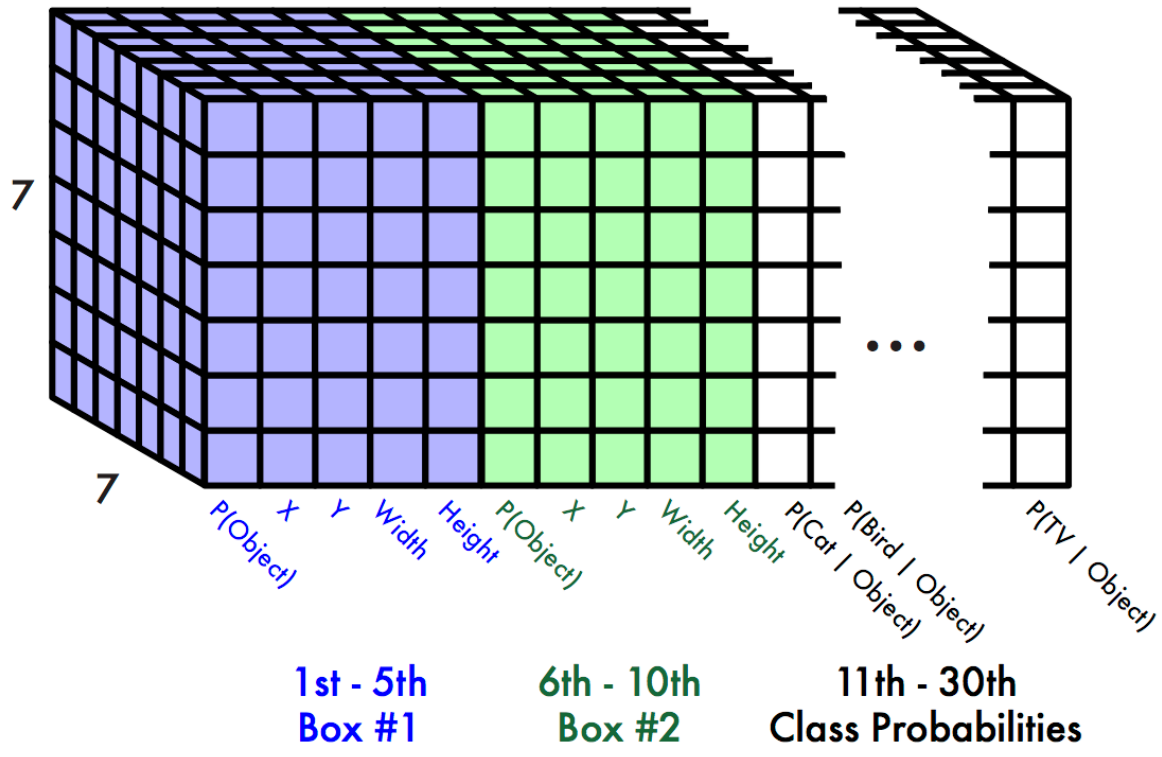
Outputs

Each cell predicts:

- For each bounding box:
  - 4 coordinates (x, y, w, h)
  - 1 confidence value
- Some number of class probabilities

For Pascal VOC:

- 7x7 grid
- 2 bounding boxes / cell
- 20 classes



Loss Function

- In training, one predictor which has the highest IoU with the ground truth is responsible

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

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

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

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

$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} \left(p_i(c) - \hat{p}_i(c) \right)^2 \qquad (3)$$

$\mathbb{1}_{ij}^{obj}$ — **The *j*th bbox predictor** in ***cell i*** is "responsible" for that prediction

$\mathbb{1}_{ij}^{noobj}$

$\mathbb{1}_{i}^{obj}$ — If object appears in ***cell i***

Note that the loss function only penalizes classification error if an object is present in that grid cell (hence the conditional class probability discussed earlier). It also only penalizes bounding box coordinate error if that predictor is "responsible" for the ground truth box (i.e. has the highest IOU of any predictor in that grid cell).

Problems

- Each grid cell can predict only B(=2) bounding boxes and one class probability
  - Not good for small objects that flock together
- Uses relatively coarse features
  - Locations of bboxes are inaccurate
- Loss function treats errors in small bbox and big bbox equally
  - Not good for scoring

SSD – Single Shot MultiBox Detector

- Current state-of-the-art object detection systems are variants of the following approach:
  - Hypothesize bounding boxes, resample pixels or features for each box, and apply a high-quality classifier.

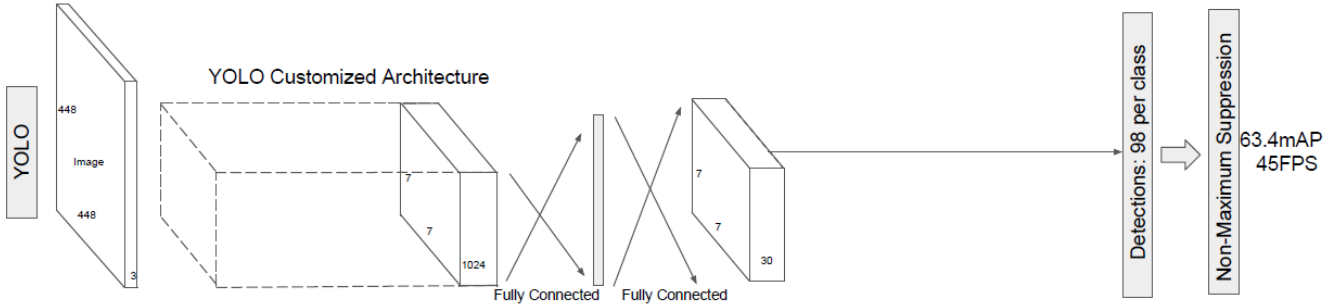
- Computationally too intensive and too slow for real-time applications.
  - Faster R-CNN operates at only 7 FPS with mAP 73.2%

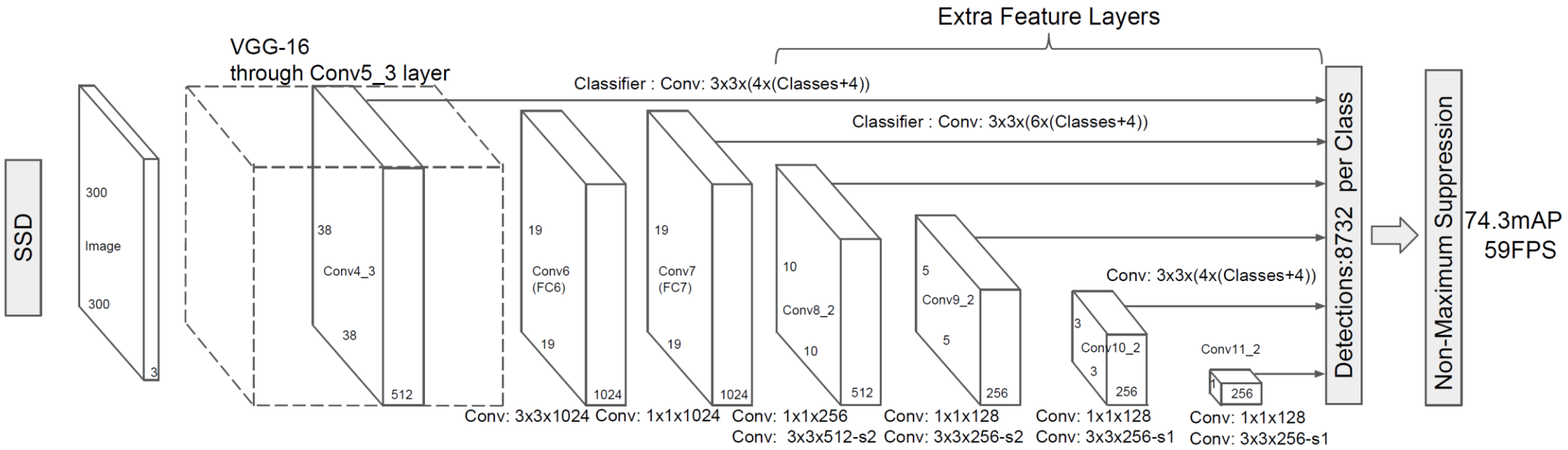
- Significantly increased speed comes only at the cost of significantly decreased detection accuracy.
  - YOLO operates at 45FPS with mAP 63.4%

Single Shot MultiBox Detector

- First deep network based object detector that does not resample pixels or features for bounding box hypotheses(1-stage) and is as accurate as approaches that do.
  - 59 FPS with mAP 74.3% on VOC2007 test

Model





Base network – VGG16

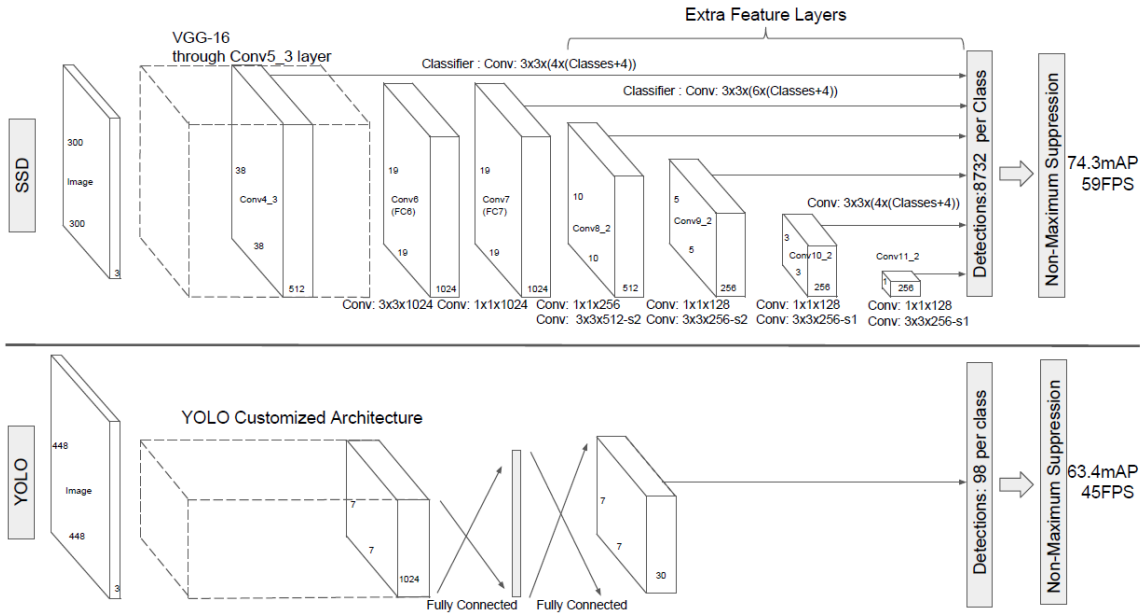
FC6 and FC7 converted to convolution layer

Auxiliary structure to produce detections

Collections of BBoxes & Scores

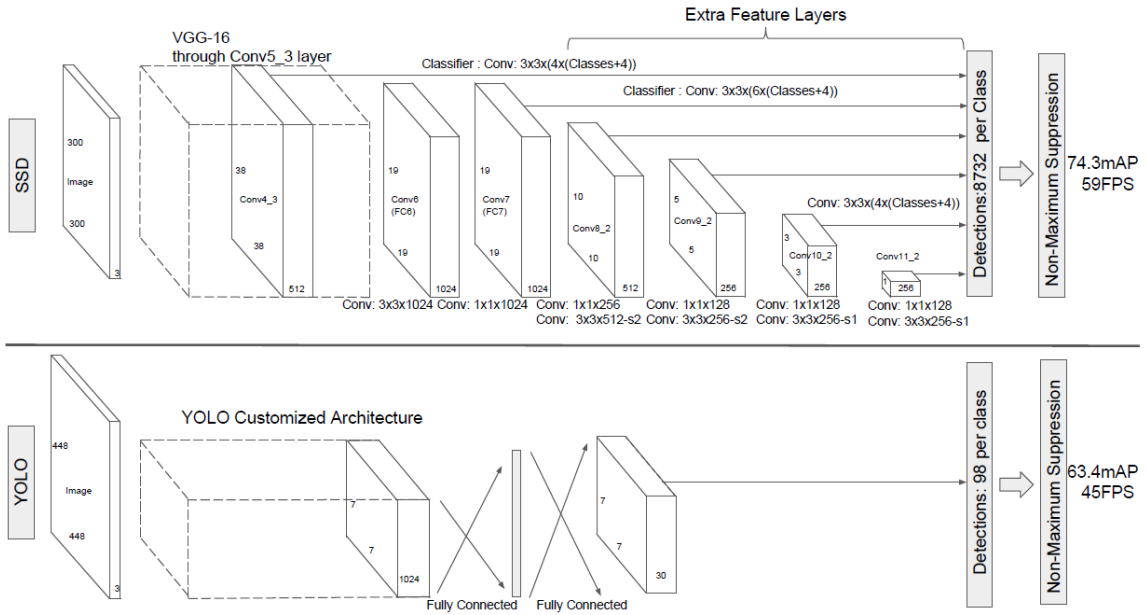
Multi-scale Feature Maps for Detection

- Adding convolutional feature layers to the end of the truncated base networks.
- These layers decrease in size progressively and allow predictions of detections at multiple scales.
  - YOLO use only single scale feature map.



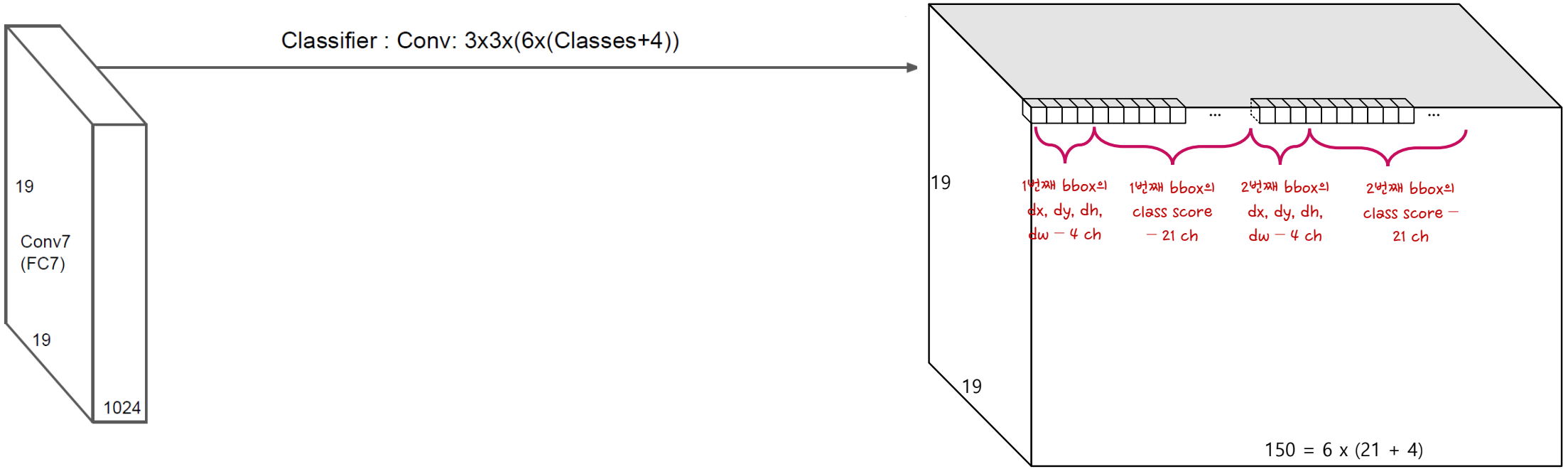
Convolutional Predictors for Detection

- For a feature layer of size m x n with p channels, the basic element for predicting parameters of a potential detection is a 3 x 3 x p small kernel that produces either a score for a category, or a shape offset relative to the default box coordinates.
  - YOLO has a fully connected layer for a score and a bbox coordinates.



Default Boxes and Aspect Ratios

- For each box out of k at a given location, we compute c class scores and the 4 offsets relative to the original default box shape.
- Total of (c+4)k filters at each location in the feature map.
- Yielding (c+4)kmn outputs for a m x n feature map.



Training – Matching Strategy

- Matching each ground truth box to the default box with the best jaccard overlap. Every ground truth box has at least 1 correspondence.
- Then, matching default boxes to any ground truth with jaccard overlap higher than a threshold(0.5).

$$\text{Jaccard Overlap} = \text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

Figure from Wikipedia

Training Objective

- Similar to Faster R-CNN

set to 1 by cross validation

$$L(x, c, l, g) = \frac{1}{N}(L_{conf}(x, c) + \alpha L_{loc}(x, l, g))$$

  - N : number of default matched bboxes
  - L_{conf} : classification loss → cross-entropy

$$L_{conf}(x, c) = -\sum_{i \in Pos}^{N} x_{ij}^{p} log(\hat{c}_i^p) - \sum_{i \in Neg} log(\hat{c}_i^0) \quad \text{where} \quad \hat{c}_i^p = \frac{\exp(c_i^p)}{\sum_p \exp(c_i^p)}$$

  - L_{loc} : localization loss → Smoth L1 loss

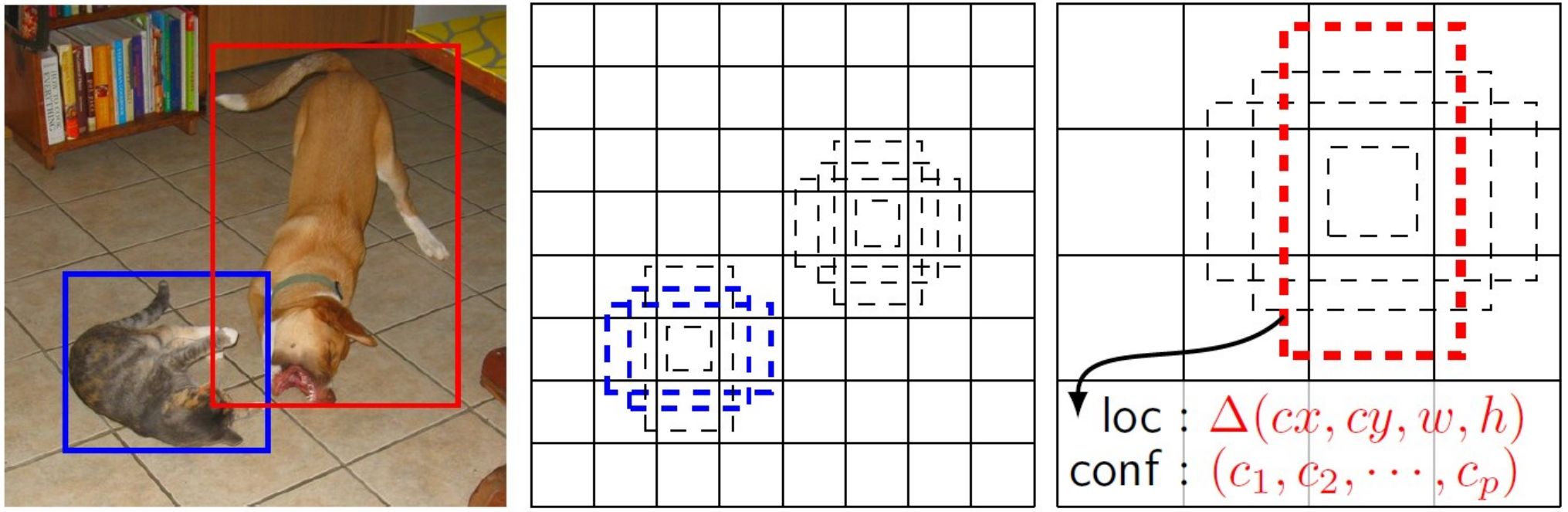
$$L_{loc}(x, l, g) = \sum_{i \in Pos}^{N} \sum_{m \in \{cx, cy, w, h\}} x_{ij}^{k} \text{smooth}_{\text{L1}}(l_i^m - \hat{g}_j^m)$$

$$\hat{g}_j^{cx} = (g_j^{cx} - d_i^{cx})/d_i^w \qquad \hat{g}_j^{cy} = (g_j^{cy} - d_i^{cy})/d_i^h$$

$$\hat{g}_j^w = \log\left(\frac{g_j^w}{d_i^w}\right) \qquad \hat{g}_j^h = \log\left(\frac{g_j^h}{d_i^h}\right)$$

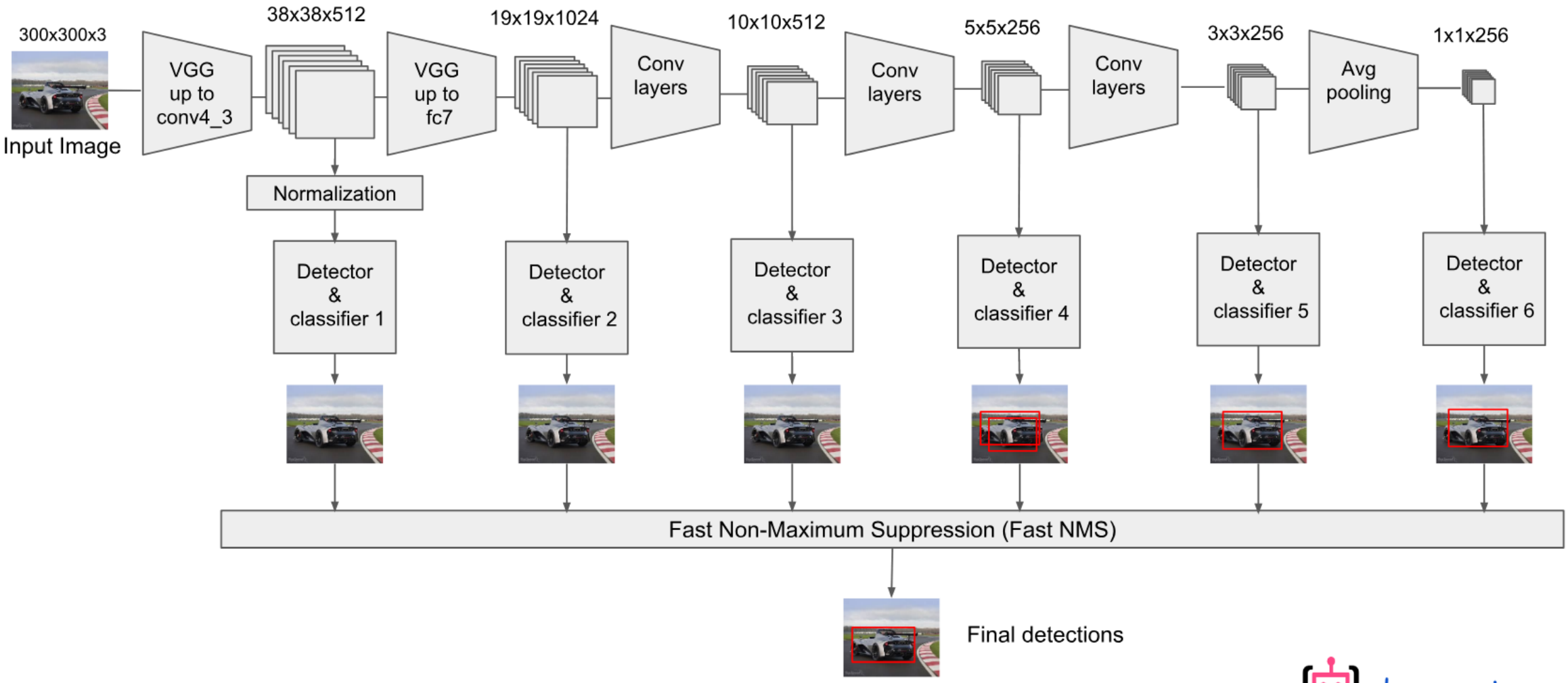
Choosing Scales and Aspect Ratios for Default Boxes

- Feature maps from different layers are used to handle scale variance.
- Specific feature map locations learn to be responsive to specific area of the image and particular scales of objects.



(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map

Choosing Scales and Aspect Ratios for Default Boxes



deepsystems.io

Slide from https://goo.gl/NsP6Wg

Choosing Scales and Aspect Ratios for Default Boxes

- If m default maps are used for prediction, the scale of the default boxes for each feature map is computed as:

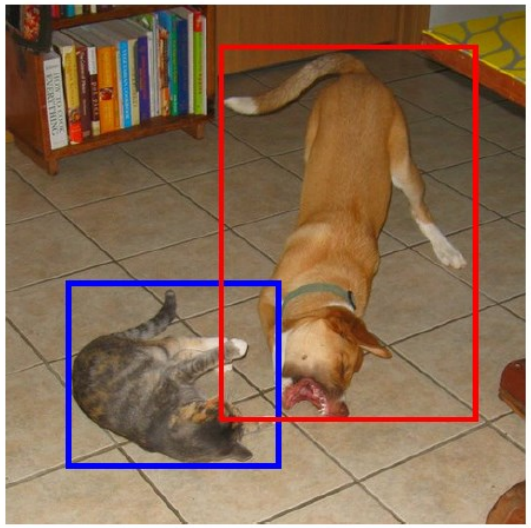
$$s_k = s_{\min} + \frac{s_{\max} - s_{\min}}{m - 1}(k - 1), \quad k \in [1, m]$$

- s_{min} is 0.2 and s_{max} is 0.9

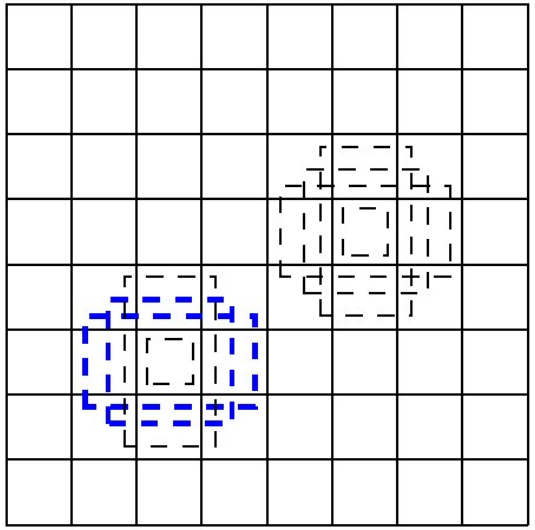
- For example (PASCAL VOC 2007)
  - s_k is 0.1, 0.2, 0.375, 0.55, 0.725. 0.9
  - means 30, 60, 112.5, 165, 217.5, 270 pixels @ input image(300x300)

Choosing Scales and Aspect Ratios for Default Boxes

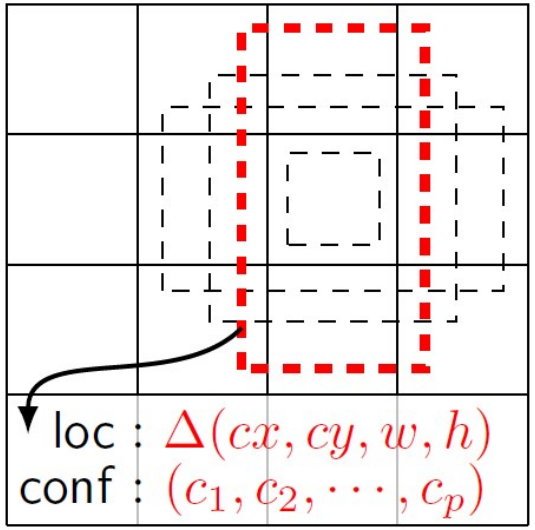
- At each scale, different aspect ratios are considered



(a) Image with GT boxes



(b) 8×8 feature map



(c) 4×4 feature map

$$a_r \in \{1, 2, 3, \frac{1}{2}, \frac{1}{3}\}$$

$$w_k^a = s_k \sqrt{a_r}$$

$$h_k^a = s_k / \sqrt{a_r}$$

For the aspect ratio of 1, one default box is added whose scale is

$$s'_k = \sqrt{s_k s_{k+1}}$$

Hard Negative Mining

- Significant imbalance between positive and negative training examples.
  - After the matching step, most of the default boxes are negatives, especially when the number of possible default boxes is large.

- Sorting them using the highest confidence loss for each default box.
- Pick the top ones so that the ratio between the negatives and positives is at most 3:1

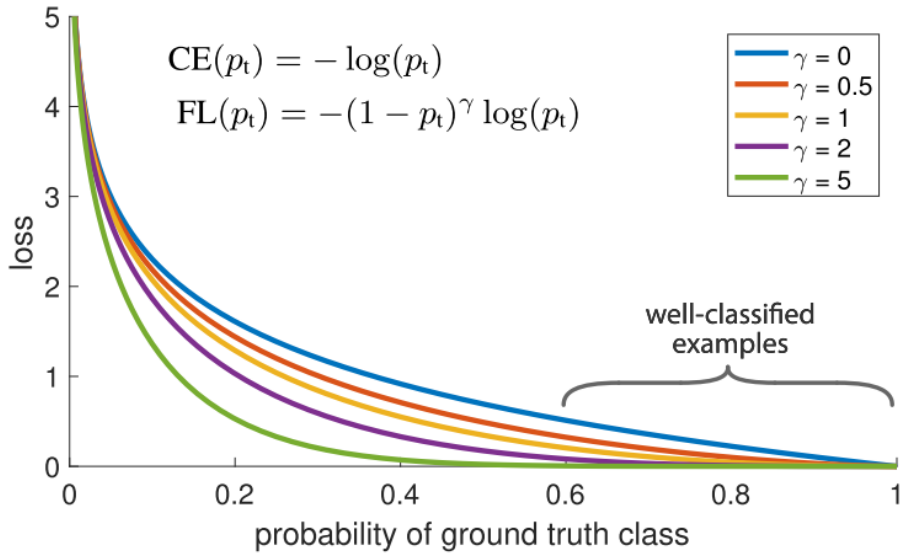
Class Imbalance Problem – RetinaNet

- Class 간의 data가 균형이 안맞는 경우
  - Weighted cross-entropy
    - Cross entropy 식에 class 별로 weight를 다르게 주어서 사용

$$L = -\sum_{C} w_c \cdot \log p$$

  - Focal Loss
    - Cross entropy에 비해 높은 확률의 경우에는 상대적으로 작은 loss를 나은 확률의 경우에는 높은 loss를 주도록 $(1\text{-}p)^{\gamma}$를 곱해줌

$$L = -\sum (1-p)^{\gamma} \cdot \log p$$



Experimental Results

- Base Network
  - VGG16 with fc6 and fc7 converted to conv layers and pool5 from 2x2 – s2 to 3x3 – s1 using atrous algorithm, removed fc8 and dropout
  - Fine-tuned using SGD with momentum

PASCAL VOC2007 Detection Results

Method	data	mAP	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv
Fast [6]	07	66.9	74.5	78.3	69.2	53.2	36.6	77.3	78.2	82.0	40.7	72.7	67.9	79.6	79.2	73.0	69.0	30.1	65.4	70.2	75.8	65.8
Fast [6]	07+12	70.0	77.0	78.1	69.3	59.4	38.3	81.6	78.6	86.7	42.8	78.8	68.9	84.7	82.0	76.6	69.9	31.8	70.1	74.8	80.4	70.4
Faster [2]	07	69.9	70.0	80.6	70.1	57.3	49.9	78.2	80.4	82.0	52.2	75.3	67.2	80.3	79.8	75.0	76.3	39.1	68.3	67.3	81.1	67.6
Faster [2]	07+12	73.2	76.5	79.0	70.9	65.5	52.1	83.1	84.7	86.4	52.0	81.9	65.7	84.8	84.6	77.5	76.7	38.8	73.6	73.9	83.0	72.6
Faster [2]	07+12+COCO	78.8	84.3	82.0	77.7	68.9	65.7	88.1	88.4	88.9	63.6	86.3	70.8	85.9	87.6	80.1	82.3	53.6	80.4	75.8	86.6	78.9
SSD300	07	68.0	73.4	77.5	64.1	59.0	38.9	75.2	80.8	78.5	46.0	67.8	69.2	76.6	82.1	77.0	72.5	41.2	64.2	69.1	78.0	68.5
SSD300	07+12	74.3	75.5	80.2	72.3	66.3	47.6	83.0	84.2	86.1	54.7	78.3	73.9	84.5	85.3	82.6	76.2	48.6	73.9	76.0	83.4	74.0
SSD300	07+12+COCO	79.6	80.9	86.3	79.0	**76.2**	57.6	87.3	88.2	88.6	60.5	85.4	**76.7**	**87.5**	**89.2**	84.5	81.4	55.0	81.9	**81.5**	85.9	78.9
SSD512	07	71.6	75.1	81.4	69.8	60.8	46.3	82.6	84.7	84.1	48.5	75.0	67.4	82.3	83.9	79.4	76.6	44.9	69.9	69.1	78.1	71.8
SSD512	07+12	76.8	82.4	84.7	78.4	73.8	53.2	86.2	87.5	86.0	57.8	83.1	70.2	84.9	85.2	83.9	79.7	50.3	77.9	73.9	82.5	75.3
SSD512	07+12+COCO	**81.6**	**86.6**	**88.3**	**82.4**	76.0	**66.3**	**88.6**	**88.9**	**89.1**	**65.1**	**88.4**	73.6	86.5	88.9	**85.3**	**84.6**	**59.1**	**85.0**	80.4	**87.4**	**81.2**

Sensitivity to Different Object Characteristics

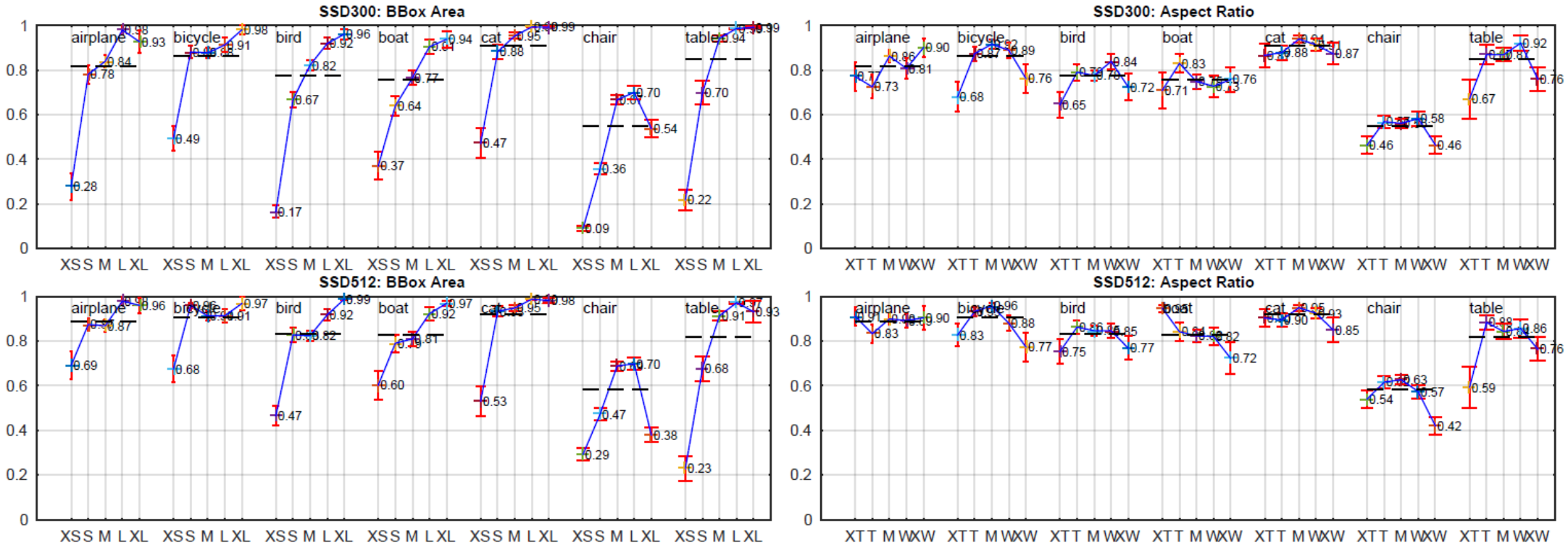
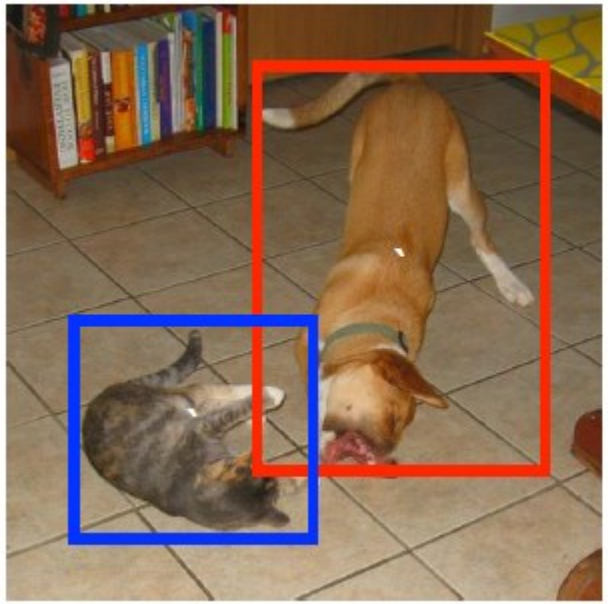
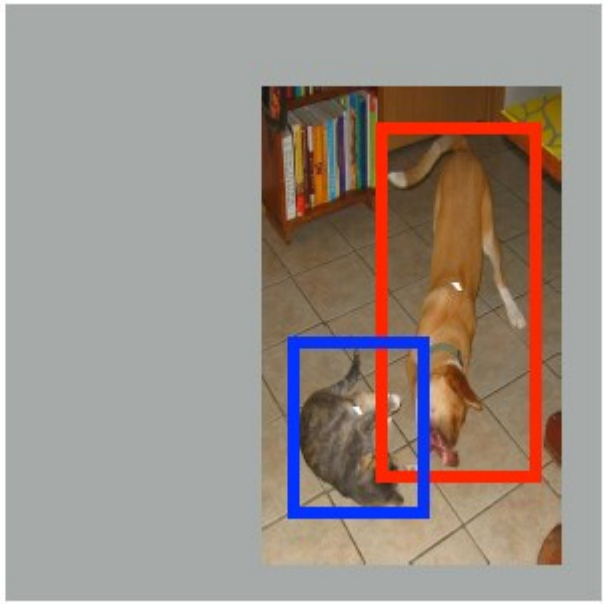


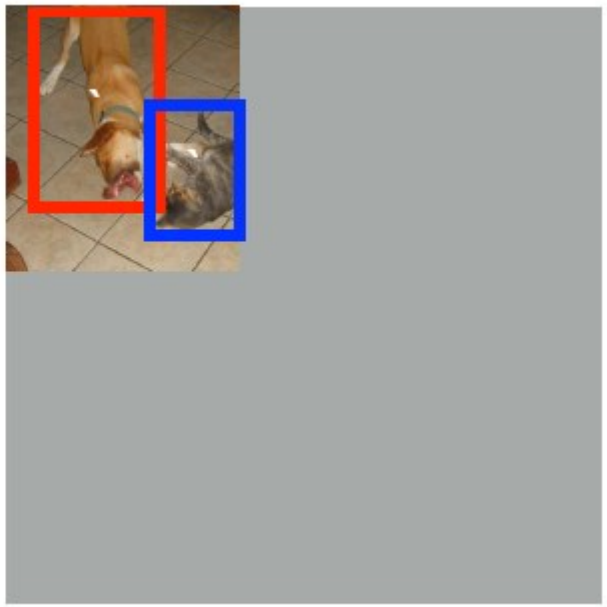
Fig. 4: **Sensitivity and impact of different object characteristics on VOC2007 `test` set using [21].** The plot on the left shows the effects of BBox Area per category, and the right plot shows the effect of Aspect Ratio. Key: BBox Area: XS=extra-small; S=small; M=medium; L=large; XL =extra-large. Aspect Ratio: XT=extra-tall/narrow; T=tall; M=medium; W=wide; XW =extra-wide.

Data Augmentation for Small Objects

- Randomly place an image on a canvas of 16 of the original image size filled with mean values before doing any random crop operation.

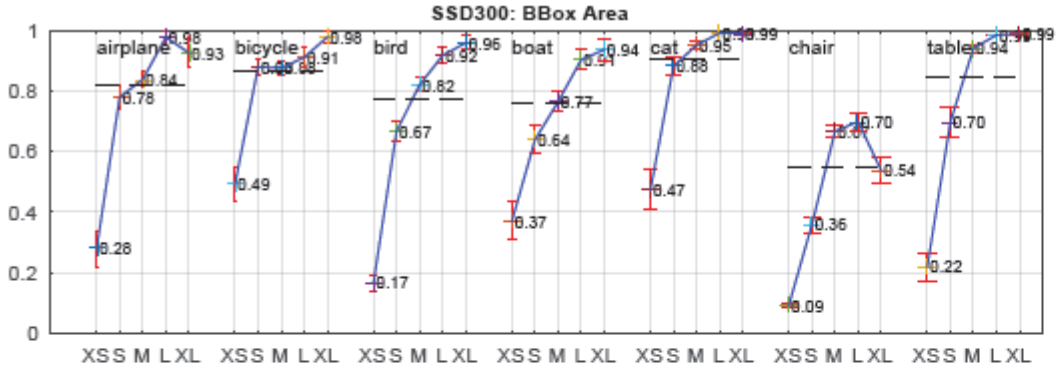


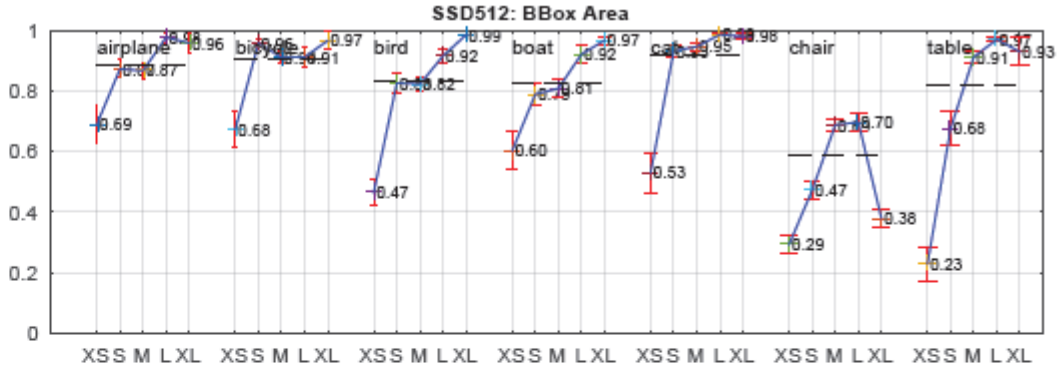


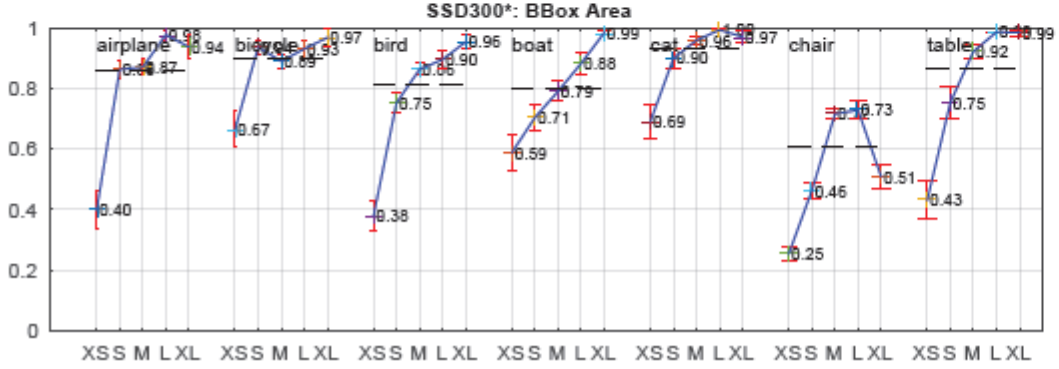


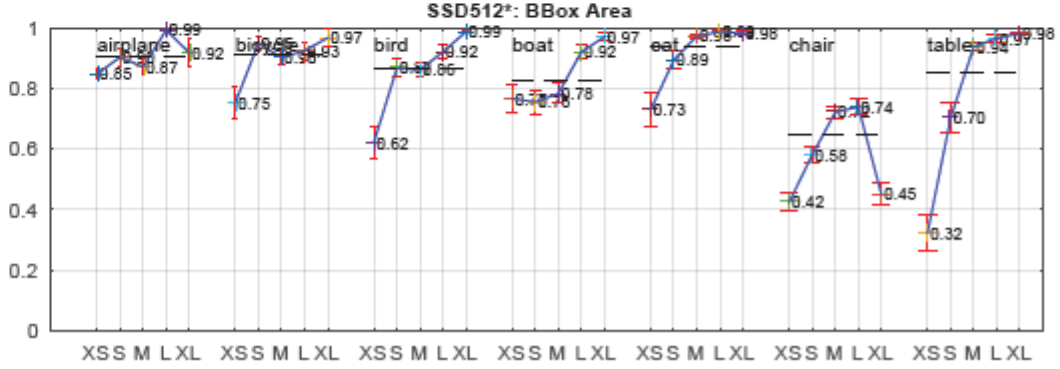
Results on Multiple Datasets with New Data Augmentation

Method	VOC2007 test		VOC2012 test		COCO test-dev2015		
	07+12	07+12+COCO	07++12	07++12+COCO	trainval35k		
	0.5	0.5	0.5	0.5	0.5:0.95	0.5	0.75
SSD300	74.3	79.6	72.4	77.5	23.2	41.2	23.4
SSD512	76.8	81.6	74.9	80.0	26.8	46.5	27.8
SSD300*	77.2	81.2	75.8	79.3	25.1	43.1	25.8
SSD512*	**79.8**	**83.2**	**78.5**	**82.2**	**28.8**	**48.5**	**30.3**









Inference Time

Method	mAP	FPS	batch size	# Boxes	Input resolution
Faster R-CNN (VGG16)	73.2	7	1	~ 6000	$\sim 1000 \times 600$
Fast YOLO	52.7	155	1	98	448×448
YOLO (VGG16)	66.4	21	1	98	448×448
SSD300	74.3	46	1	8732	300×300
SSD512	76.8	19	1	24564	512×512
SSD300	74.3	59	8	8732	300×300
SSD512	76.8	22	8	24564	512×512